# Morphological Disambiguation using Probabilistic Sequence Models

## Miikka Pietari Silfverberg

*Academic dissertation to be publicly discussed, by due permission of the Faculty of Arts at the University of Helsinki in auditorium FOO (in lecture room QUUX), on the $XY^{th}$ of February at 12 o'clock.*

University of Helsinki
Finland

**Supervisor**

Krister Lindén, Helsingin yliopisto, Finland, Anssi Yli-Jyrä, Helsingin yliopisto, Finland

**Pre-examiners**

XYZ, FOO, BAR
XYZ, FOO, BAR

**Opponent**

XYZ, FOO, BAR

**Custos**

XYZ, FOO, BAR

**Contact information**

Department of Modern Languages
P.O. Box 24 (Unioninkatu 40)
FI-00014 University of Helsinki
Finland

Email address: postmaster@helsinki.fi
URL: http://www.helsinki.fi/
Telephone: +358 9 1911, telefax: +358 9 191 51120

*Nobody is going to read your PhD thesis*

*Ancient Proverb*

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# Notation

<div align="center">Acronyms</div>

| | |
|---|---|
| CRF | Conditional Random Field |
| HMM | Hidden Markov Model |
| MEMM | Maximum-Entropy Markov Model |
| NB | Naïve Bayes |
| PGM | Probabilistic Graphical Model |
| POS | Part-of-Speech |
| MAP | Maximum a posteriori |

<div align="center">Mathematical Notation</div>

| | |
|---|---|
| $x[1:t]$ | Prefix $(x_1, \ ..., \ x_t)$ of sequence $x = (x_1, \ ..., \ x_t, \ ..., \ x_T)$. |
| $X^t$ | The cartesian product of $t$ copies of the set $X$. |

# Acknowledgements

Teemu Ruokolainen statistical methods, friendship, writing.

Måns Huldén finite-state, statistical methods, inspiration, courage, IPA.

Krister Lindén ideas, letting me do useless stuff once in a while, pushing me forward, encouragement, realism.

Anssi Yli-Jyrä inspiration, finite-state, positive attitude, friendship.

Kimmo Koskenniemi intellectual rigorosity, how to think of stuff, how to be legible, being critical.

Arto Voutilainen

Erik Axelson

Tommi Pirinen

Senka Drobac

Sam Hardwick

Graham Wilcock

Juliette Kennedy

Panu Kalliokoski

Coursera

Reetta Vuokko-Syrjänen and Kaj Syrjänen + Elsa

Family

Veera Nykänen

Jarmo Widemann

Antti, Sami, Ville, Jarmo, Rod, Marko and many more friends who have brought a lot of happiness through the time I've been working on this thesis project.

# Chapter 1

# Introduction

# Chapter 2

# Morphology

## 2.1   The Structure of Words

- The morphological system.

- Word, morpheme, lemma, stem.

- Word classes.

- Inflectional categories.

## 2.2   Languages with Rich Morphology

- Typological classification of languages.

- "Large label sets".

## 2.3   Morphological Analyzers

- Finite-state morphology (Koskenniemi, 1984), (Kaplan and Kay, 1994).

# Chapter 3

# Machine Learning

This section outlines the basic methodology followed in machine learning approaches to Natural Language Processing. I will briefly discuss machine learning from a general point of view and then present supervised machine learning in more detail using linear regression as example. I will then present on the different kinds of classifiers applied in NLP; both unstructured and structured.

### 3.0.1 Overview

Approaches to Natural Language Processing can be broadly divided into two groups: rule-based and machine learning approaches. Rule-based approaches utilize hand crafted rules for tasks such as text labeling or machine translation. Machine learning approaches solve the same set of problems using data driven (usually statistically motivated) models and samples from the problem domain, which are used to estimate model parameters.

This thesis focuses on extending machine learning techniques to the domain of morphologically complex languages, where they have been applied less frequent than for morphologically more straightforward languages like English. I want to emphasize that the thesis should not be seen as an attack against the rule-based paradigm for Natural Language Processing. It is simply an investigation into extension of machine learning techniques.

Machine learning and hand crafted rules have their respective merits and short-comings. Rule-based methods can often give much better results and so on.

Machine Learning is can be divided into two fields supervised and unsupervised Machine Learning. Supervised machine translation uses a training material with hand crafted annotations. An example would be a set of images with associated key words, where the

task is to build a system which can associate previously unseen images with appropriate key words.

Supervised machine learning is typically employed for tasks such as labeling (that is classification) and translation. Typical examples of tasks include Part-of-Speech labeling and speech recognition where annotations consist of POS labels for the words in some text and written sentences corresponding to an acoustic speech signal respectively.

In contrast to supervised machine translation, unsupervised approaches exclusively utilize unannotated data. Unsupervised machine learning is most often used for various kinds of clustering tasks, that is grouping sets of examples into subsets of similar examples.

In Natural Language processing, supervised learning approaches are most often used (for example ...). Unsupervised approaches, however, can also be useful for e.g. exploratory data analysis (...).

This thesis focuses on supervised machine learning.

## 3.1   Supervised Learning

In this section, I will illustrate the key concepts and techniques in supervised Machine Learning using the simple example of linear regression. I will explain the plain linear regression model and show how it can be fitted using training data. I will then briefly present ridge regression which is a regularized version of linear regression.

I chose linear regression as example because it is a simple model yet can be used to illustrate data driven techniques. Moreover, the model has several tractable properties such as smoothness and convexity. Additionally, it can be seen as the simplest example of a linear classifier which is a category of models encompassing

### 3.1.1   Basic Concepts

**Linear Regression**    As a simple example, imagine a person called Jill who is a real estate agent. She is interested in constructing an application, for use by prospective clients, which would give rough estimates for the selling price of a property. Jill knows that a large number of factors affect housing prices but there are a few very robust quantifiable predictors of price that are easy to measure.

Jill decides to base the model on the following predictors:

1. The living area.

2. The number of rooms.

3. The number of bathrooms.

4. Size of the yard.

5. Distance of the house from the city center.

6. Age of the house.

7. Amount of time since the last major renovation.

Jill decides to use the simplest model which seems reasonable. This model is *linear regression* which models *the dependent variable* house price as a linear combination of the independent variables listed above and parameter values in $\mathbb{R}$. The linear regression model is probably not accurate. It fails in several regards. For example, increasing age of the house probably reduces the price up to a point but very old houses can in fact be more expensive then newly built houses especially if they have been renovated lately. Although, the linear model is unlikely to be entirely accurate, Jill is happy with it because the intention is just to give a ball park estimate of the price for the average prospective client.

To formalize the linear regression model, let us call the dependent variable price $y$ and each of the independent variables living area, number of rooms and so on $x_i$. Given a vector $x = (x[1], ..., x[n])^\top \in \mathbb{R}^n$, which combines the independent variables[1], and a parameter vector $\theta \in \mathbb{R}^n$ the linear regression model is given in Equation 3.1.

$$y(x; \theta) = x^\top \theta \tag{3.1}$$

Two questions immediately arise: How to compute the price given parameters and predictors and how to compute the parameter vector $\theta$. These questions are common for all supervised learning problems also when using other models than the linear regression model.

**Inference**   The first question concerns *inference*, that is finding the most likely value for the dependent variable given the independent variables. In the case of linear regression, the answer to this question is straightforward. To compute the price, simply perform the

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[1]In reality, each of the predictors would probably be transformed to give all of them the same average and variance. Although this ii not required in theory, it tends to give a better model **?**.

inner product in Equation 3.1. The question is, however, not entirely settled because one might also ask for example how close to the actual price the estimate $y$ is likely to be. A related question would be to provide an upper and lower bound for the price so that the actual price is very likely to be inside the provided bounds. To answer these questions, one would have to model the expected error.

Inference is very easy and also efficient in the case of linear regression. With more complex model such as structured graphical models used in this thesis, it can however be an algorithmically and computationally more challenging problem. The principle is still the same: Find the $y$ which is most likely given the input parameters.

**Estimation**   The second question concerns *estimation of model parameters* and it is more complex than the question of inference. First of all, Jill needs training data. She also needs to decide upon an *estimator*, that is, a method for estimating the parameters $\theta$.

In the case of house price prediction, Jill can simply use data about houses she has brokered in the past. She decides to use a training data set $\mathcal{D} = \{(x_1, y_1), ..., (x_T, y_T)\}$, where each $x_t = (x_t[1]...x_t[n])$ is a vector of independent variable values (living area, age of the house and so on) and $y_t$ is the dependent variable value, that is the final selling price of the house. Now Jill needs to make a choice. How many training examples $(x_t, y_t)$ does she need? The common wisdom is that more data is always better, however, this has bearing on how the parameters need to be estimated. In any case, the number of data points in the training data should ideally be higher than the number of parameters that need to be estimated. When one cannot accomplish this, one encounters the so called *data sparsity problem*.

**Data Sparsity**   Whereas getting sufficient training data is fairly easy in the case of housing prices, it is vastly more difficult to accomplish with more complicated models in natural language processing. Therefore, one central question in this thesis is how to counteract *data sparsity*.

**Cost Functions**   The objective in estimation is to find a parameter vector $\theta$ which in some sense minimizes the error of the house price predictions $y(x_t; \theta)$ when compared to the actual realized house prices $y_t$ in the training data. The usual minimization criterion used with linear regression is the least square sum criterion given in Equation 3.2. It is minimized by a parameter vector $\theta$ which gives as small square errors $|y_t - y(x_t; \theta)|^2$ as possible.

$$\theta = \operatorname*{arg\,min}_{\theta' \in \mathbb{R}^n} \sum_{x_t \in \mathcal{D}} |y_t - y(x_t; \theta')|^2 \qquad (3.2)$$

The square sum is an example of a *cost function* (also called the objective function). A cost function assigns a non-negative real cost for each parameter vector. Using the concept of cost function, the objective of estimation can be reformulated: Find the parameter vector $\theta$ that minimizes the cost of the training data.

**The Exact Solution** In the case of linear regression, there is a well known exact solution for $\theta$ which utilizes linear algebra. The solution is given in Equation 3.3. The matrix $X \in \mathbb{R}^T_n$ is defined by $X_{t,i} = x_t[i]$ and its More-Pennrose pseudoinverse $X^+ \in \mathbb{R}^n_T$ is defined as $X^+ = (X^\top X)^{-1} X^\top$. The vector $Y \in R^T$ is simply the vector of realized house prices $y_t$. The solution $\theta$ exists only when none of the independent variables are linear combinations of each other in the training data.

$$\theta = X^+ Y \qquad (3.3)$$

**Iterative Estimation** Although the linear regression model is simple enough so that it can be estimated exactly, the same does not hold for most more complex models such as the Conditional Random Field investigated in this thesis. Moreover, the exact solution might often not be the one that is desired. Often the training data is quite sparse, that is there is too little of it compared to the amount of parameters that need to be estimated. Therefore, the model may *over-fit* the training data and fail to generalize well to examples not included in the training data.

**Regularization** Due to the problem of over-fitting, a family of heuristic techniques called *regularization* is often employed. They aim to transform the original problem in a way which will penalize both deviance from the gold standard and "complexity" of the solution $\theta$. Regularization can be seen to convey the same idea as Occam's Maxim which states that a simpler explanation for a phenomenon should be preferred when compared to a more complex explanation yielding equivalent results. Of course, this does not explain what is meant by a "complex" parameter vector $\theta$.

To illustrate simple and complex parameter vectors, examine a case of linear regression where the dependent variable $y$ and the predictors $x_i$ have mean $0$ and variance $1$ in the training data. This may seem restrictive but in fact any linear regression problem can

easily be transformed into this form by applying an affine transformation $z \mapsto az - b$. When doing inference, this affine transformation can simply be reversed by applying $z \mapsto a^{-1}(z + b)$. The simplest parameter vector $\theta$ is clearly the zero vector $\theta = (0...0)^{\top}$. It corresponds to the hypothesis that the predictors $x_i$ have no effect on the dependent variable $y$. According to this hypothesis, the prediction is always the average of the dependent variable values in the training data.

The zero solution to a linear regression problem is simple but also totally biased. Because we are assuming that the independent variables $x_i$ explain the dependent variable $y$, a model that completely disregards them is unlikely to give a good fit to the training data. By introducing a regularization term into the cost function, we can however encourage simple solutions while at the same time also preferring solutions that give a good fit. There are several ways to accomplish this but the most commonly used are so called $L_1$ and $L_2$ regularization. These are general regularization methods that are employed in many models in machine learning.

The $L_1$ regularized cost function for linear regression is given in Equation 3.4. $L_1$ regularization, also called LASSO regularization **?**, enforces solutions where many of the parameter values are $0$. These are also called sparse parameters. It is suitable in the situation where the model is over specified, that is, many of the predictors might not be necessary for good prediction. The expression is a sum

$$\theta = \underset{\theta' \in \mathbb{R}^n}{\arg\min} \sum_{x_t \in \mathcal{D}} |y_t - y(x_t; \theta')|^2 + \lambda \sum_i |\theta[i]| \tag{3.4}$$

The $L_2$ regularized cost function is given in 3.5. $L_2$ regularization is also called Tikhonov regularization. In contrast to $L_1$ regularization, it directly prefers solutions with small norm. A linear regression model with Tikhonov regularization is called a ridge regression model.

$$\theta = \underset{\theta' \in \mathbb{R}^n}{\arg\min} \sum_{x_t \in \mathcal{D}} |y_t - y(x_t; \theta')|^2 + \lambda \|\theta\|^2 = \underset{\theta' \in \mathbb{R}^n}{\arg\min} \sum_{x_t \in \mathcal{D}} |y_t - y(x_t; \theta')|^2 + \lambda \sum_i |\theta[i]|^2 \tag{3.5}$$

The coefficient $\lambda \in \mathbb{R}^+$ is called the *regularizer*. The regularizer determines the degree to which model fit and simplicity affect the cost. A higher $\lambda$ will increase the cost for complex models more than a lower one. When $\lambda$ increases, the optimal parameter vector $\theta$ approaches the zero vector and when it decreases $\theta$ approaches the parameters

that fit the training data as closely as possible. This is called under-fitting.

The regularizer is a so called *hyper-parameter* of the regularized liner regression model. It is easy to see that increasing $\lambda$ will automatically increase the cost. Therefore, there is no direct way to estimate its correct magnitude simply using the training data. Instead *held-out data* can be used. Held-out data is labeled data that is not used directly for estimating model parameters. If the model over-fits the training data, that is generalizes poorly to unseen examples, the held-out data will have a high cost. However, it will also have a high cost if the model under-fits, that is, performs poorly on all data. Held-out data can therefore be used to find an optimal values for the regularizer $\lambda$. Often one tries several potential values and chooses the one that minimizes the cost of the held-out data. Usually, one uses the unregularized cost function for the held-out data.

**Iterative Estimation**   Regularization is an additional reason for introducing iterative estimation methods instead of exact estimation. There are several choices of regularizers and some of them might not result in optimization problems that have closed form solutions[2]. When an exact solution cannot be computed, or it is undesirable, numerical methods can be used to estimate model parameters.

- Smoothness of cost function.

- Convexity.

- Compactness. Not getting stuck at local optima does not guarantee that a global optimum can be found.

- Stochastic Gradient Descent.

- Quasi Newton Methods.

## 3.2   Classifiers

- Naïve Bayes' classifier.

- Generative and Discriminative Classifiers.

- Linear classifiers: logistic classifier, perceptron classifier (Freund and Schapire, 1999), SVM (Cortes and Vapnik, 1995).

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[2]In the case of regression, non-linear *kernel functions* also result in optimization problems that don't have a closed form solution. I will elaborate this when discussing logistic regression.

## 3.3   Structured Classifiers

- The idea of chained stochastic processes.

- Markov chain.

- HMM

- MEMM

- CRF

# Chapter 4

# Part-of-Speech Tagging

## 4.1 Background

## 4.2 Statistical Part-of-Speech Taggers

Morphological disambiguation and part-of-speech tagging are interesting tasks from the perspective of machine learning because they represent labeling tasks where both the set of inputs and outputs are unfathomably large. Since each word in a sentence $x = (x_1, ..., x_T)$ of length $T$ receives one label, the complete sentence has $n^T$ possible labels $y = (y_1, ..., y_T)$ when the POS label set has size $n$.

The exact number of potential English sentences of any given length, say ten, is difficult to estimate because all strings of words are not valid sentences[1]. However, it is safe to say that it is very large – indeed much larger than the combined number of sentences in POS annotated English language corpora humankind is likely to ever produce. Direct ML-estimation of the conditional distributions $p(y \mid x)$, for POS label sequences $y$ and sentences $x$, by counting is therefore impossible.

Because the POS labels of words in a sentence depend on each other, predicting the label $y_t$ for each position $t$ separately is not an optimal solution. Consider the sentence "The police dog me constantly although I haven't done anything wrong!".

The labels of the adjacent words "police", "dog", "me" and "constantly" help to disambiguate each other. A priori, we think that "dog" is a noun since the verb "dog" is quite rare. This hypothesis is supported by the preceding word "police" because "police dog" is an established noun–noun collocation. However, the next word "me" can only be

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[1]Moreover, it is not easy to say how many word types the English language includes.

a pronoun, which brings this interpretation into question. The fourth word "constantly" is an adverb, which provides additional evidence against a noun interpretation of "dog". In total, the evidence points toward a verb interpretation for "dog".

The disambiguation of the POS label for "dog" utilizes both so called *unstructured* and *structured* information. The information that "police dog" is a frequent nominal compound is unstructured information, because it refers only to the POS label (the prediction) of the word "dog". The information that verbs are much more likely to be followed by pronouns than nouns is a piece of structured information because it refers to the combination of several POS labels. Structured information refers to the combination of predictions. Both kinds of information are very useful, but a model which predicts the label $y_t$ for each position in isolation cannot utilize structured information.

Even though structured information is useful, structure is probably mostly useful in a limited way. For example the labels of "dog" and "anything" in the example are not especially helpful for disambiguating each other. It is probably a sensible assumption that the further apart two words are situated in the sentence, the less likely it is that they can significantly aid in disambiguating each other. However, this does not mean that the interpretations of words that are far apart cannot depend on each other – in fact they frequently do. For example embedded clauses introduce long range dependencies inside sentences.

It is said that machine learning is sophisticated counting of co-occurrences. This statement applies extremely well to POS tagging. Counting is an adequate approach to capturing correlations between the labels of words inside a small window (in the league of five words), because most adjacent words indeed do depend on each other is some way. However, sophisticated counting fails for larger windows, because the number of meaningful dependencies in large windows is negligible in comparison to the space of possibilities.

## 4.3   Morphological Disambiguation

# Chapter 5

# Hidden Markov Models

AN INTRO

## 5.1   Example

I will illustrate Hidden Markov Models using an example. Imagine a person called Jill who is hospitalized and occupies a windowless room. The only way for her to know what is happening in the outside world is to observe a nurse who passes her room daily[1].

Suppose, Jill is interested in weather phenomena and she decides to pass time by guessing if it is raining outside. She bases her guesses on whether or not the nurse is carrying an umbrella. In other words, she predicts an unobserved variable, the weather, based on an observed variable, the nurse's umbrella.

There are several probabilistic models Jill might use. The simplest useful model assigns probability $1$ to the event of rain, if the nurse carries an umbrella, and assign it the probability $0$ otherwise. This simplistic model would certainly give the correct prediction most of the time, but Jill believes that she can do better.

Jill knows that people often carry an umbrella when it is raining. She also knows that they rarely carry one when the weather is clear. However, people sometimes do forget their umbrella on rainy days, perhaps because they are in a hurry. Moreover, people sometimes carry an umbrella even when it is not raining. For example the weather might be murky and they might anticipate rain. Therefore, Jill decides to reserve some probability, say $0.2$, for the event that the nurse is carrying an umbrella when the weather is clear. She reserves an equal probability for the event that the nurse arrives at work without an

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[1]To make things simple, imagine the nurse never gets a day off.

umbrella although it is in fact raining.

Without additional information, this more complicated model will give exactly the same MAP predictions as the simplistic one. Knowledge of meteorology, however, also factors in. Let us suppose Jill is a weather enthusiast and she knows that the probability of rain is $0.25$ a priori, making the probability of clear weather $0.75$. She also knows that the probability of rain increases markedly on days following rainy days at which time it is $0.7$. Similarly, the probability of clear weather increases to $0.9$ if the weather was clear on the previous day. Figure 5.1 summarizes these probabilities.[2]

| $\iota$ | | | $T$ | CLEAR | RAIN | | $E$ | ![clear] | ![umbrella] |
|---|---|---|---|---|---|---|---|---|---|
| CLEAR | 0.75 | | CLEAR | 0.9 | 0.1 | | CLEAR | 0.8 | 0.2 |
| RAIN | 0.25 | | RAIN | 0.3 | 0.7 | | RAIN | 0.2 | 0.8 |

Figure 5.1: Foo FIXME

Let us assume that Jill observes the nurse for one week. She sees the nurse carry an umbrella on all days except Tuesday. The MAP prediction given by the simplistic model is that Tuesday is clear and all other days are rainy. The more complex model will, however, give a different MAP prediction: the probability is maximized by assuming that all days are rainy. Under the more complex model, it is simply more likely that the nurse forgot to bring an umbrella on Tuesday.

Figure 5.2: Foo
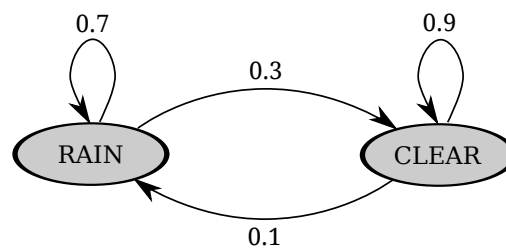


The model Jill is using for weather prediction is called a Hidden Markov Model. It can be used to make predictions about a series of events based on indirect observations.

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[2]Since the author of this thesis has very little knowledge about meteorology, these probabilities are likely to be nonsense. The overall probability of rain and clear weather is, however, chosen to be the steady state of the Markov chain determined by the probabilities of transitioning between states. Consistency is therefore maintained.

The HMM is commonly visualized as a directed graph. Each hidden state, for example Rain and Clear, represents a vertex in the graph. Transitions from one hidden state to another are represented by arrows labeled with probabilities. Figure 5.2 shows a graph representing the transition structure of the HMM outlined in Figure 5.1.

## 5.2  Formal Definition

Abstracting from the example above, an HMM is a probabilistic model that generates sequences of state-observation pairs. At each step $t$ in the generation process, the model generates an observation by sampling the *emission distribution* $\varepsilon_{y_t}$ of the current state $y_t$. It will then generate a successor state $y_{t+1}$ by sampling the *transition distribution* $\tau_{y_t}$ of state $y_t$. The first hidden state $y_1$ is sampled from the *initial distribution* $\iota$ of the HMM.

Since the succession of days is infinite for all practical purposes, there was no need to consider termination in the example presented in Figure 5.2. Nevertheless, many processes, such as sentences, do have finite duration. Therefore, a special *final state* $f$ is required. When the process arrives at the final state, it stops: no observations or successor states are generated.

Following Rabiner (1989), I formally define a *discrete* HMM as a structure $(Y, X, i, T, E, F)$ where:

1. $Y$ is the set of hidden states ($Y = \{\mathrm{CLEAR}, \mathrm{RAIN}\}$ in the example in Figure 5.1).

2. $X$ is the set of emissions, also called observations ( $X = \{\text{🏖}, \text{☂}\}$ in the example in Figure 5.1).

3. $\iota : Y \to \mathbb{R}$ is the initial state distribution, that is the probability distribution determining the initial state of an HMM process (array $\iota$ in Figure 5.1).

4. $T$ is the collection of transition distributions, $\tau_y : Y \to \mathbb{R}$, that determine the probability of transitioning from a state $y$ to each state $y' \in Y$ (array $T$ in Figure 5.1).

5. $E$ is the collection of emission distributions $\varepsilon_y : X \to \mathbb{R}$, which determine the probability of observing each emission $o \in X$ in state $y \in Y$ (array $E$ in Figure 5.1).

6. $f \in Y$ is the final state. The state $f$ emits no observations and there are no transitions from $f$.

The definition of HMMs in this thesis differs slightly from Rabiner (1989) since I utilize final states. Final states were used in for example **?**. Absorbing states **?** could also be used. FIXME.

Figure 5.3 is a more accurate description of the HMM in Figure 5.1 than Figure 5.2. The image has been augmented with initial distribution and a final state.

Because the progression of days is infinite for all practical purposes, the probability of transitioning to the final state $f$ in example 5.2 is 0 regardless of the current state. Hence, the probability of any single sequence of states and emissions is 0. Still, the probability of an initial segment of a state sequence may still be non-zero[3].

Figure 5.3: Foo
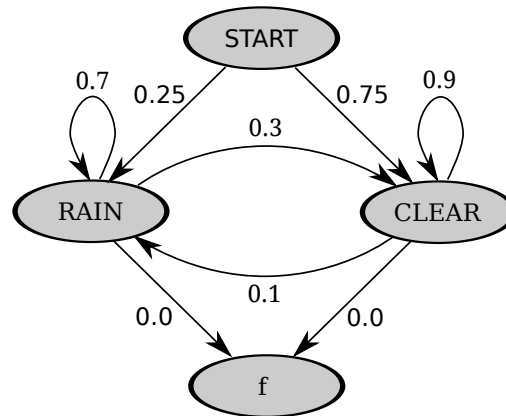


An HMM models a number of useful quantities:

1. The *joint probability* $p(x, y; \theta)$ of a observation sequence $x$ and state sequence $y$. This is the probability that an HMM with parameters $\theta$ will generate the state sequence $y$ and generate the observation $x_t$ in every state $y_t$.

2. The *marginal probability* $p(x; \theta)$ of an observation sequence $x$. This is the overall probability that the observation sequence generated by an HMM is $x$.

3. The *conditional probability* $p(y \mid x; \theta)$ of a state sequence $y$ given an observation sequence $x$. That is, how likely it is that the model passes through the states in $y$ when emitting the observations in $x$ in order.

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[3]The probability of an initial segment up to position $t$ can be computed using the forward algorithm, which is presented in Section 5.3.1.

4. The *marginal probability $p(z, t, \ x; \theta)$ of state $z$ at position $t$* when emitting the observation sequence $x$. That is, the probability of emitting observation sequence $x$ under the single constraint that the state at position $t$ has to be $z$.

To formally define these probabilities, let $\theta = \{\iota, \ T, \ E\}$ be the parameters of some HMM with observation set $X$ and hidden state set $Y$, $x = (x_1, \ ..., \ x_T) \in X^T$ be a sequence of observations and $y = (y_1, \ ..., \ y_T, y_{t+1} = f) \in Y^{T+1}$ a sequence of hidden states. Note, that the last state in $y$ has to be the final state $f$. Then the joint probability $p(x, y; \theta)$ of $x$ and $y$ given $\theta$ is defined by Equation (5.1).

$$p(x, y; \theta) = p(y; \theta) \cdot p(x \mid y; \theta) = \left( \iota(y_1) \cdot \prod_{t=1}^{T} \tau_{y_t}(y_{t+1}) \right) \cdot \prod_{t=1}^{T} \varepsilon_{y_t}(x_t) \qquad (5.1)$$

Equation (5.1) is a product of two factors: the probability of the hidden state sequence $y$, determined by the initial and transition probabilities, and the probability of the emissions $x_t$ given hidden states $y_t$ determined by the emission probabilities.

FIXME: Talk about language models and stuff.

There is no limit on the number of hidden states in $Y$ that can emit a given observation. Therefore, it is quite possible that several state sequence $y \in Y^{T+1}$ can be generate the same sequence of observations $x \in X^T$. The marginal probability $p(x; \theta)$ of an observation sequence $x$ can be found by summing over all state sequences that could have generated $x$. It is defined by Equation (5.2).

$$p(x; \theta) = \sum_{y \in Y^{T+1}, \ y_{T+1}=f} p(x, y; \theta) \qquad (5.2)$$

Possibly the most important probability associated to the HMM is the conditional probability $p(y \mid x; \theta)$ of state sequence $y$ given observations $x$. This is an important quantity because maximizing $p(y \mid x; \theta)$ with regard to $y$ will give the MAP assignment of observation sequence $x$. It is defined by Equation (5.3).

$$p(y \mid x; \theta) = \frac{p(x, y; \theta)}{p(x; \theta)} \qquad (5.3)$$

It is noteworthy, that $p(y \mid x; \theta) \propto p(x, y; \theta)$ because the marginal probability $p(x; \theta)$ is independent of $y$. Therefore, $y$ maximizes $p(y \mid x; \theta)$ if and only if, it maximizes $p(x, y; \theta)$. This facilitates inference.

Finally, the posterior marginal probability of state $z$ at position $t$ given the observation

sequence $x$ is computed by summing, or marginalizing, over all state sequence $y$, where $y_t = z$. It is defined by Equation (5.4)

$$p(z, t, \ x; \theta) = \sum_{y' \in Y^{T+1}, \ y'_t = z, \ y'_{T+1} = f} p(x, y'; \theta) \tag{5.4}$$

## 5.3　Inference

Informally, inference in HMMs means finding a maximally probable sequence of hidden states $y$ that might have emitted the observation $x$. As Rabiner (1989) points out, this statement is not strong enough to suggest an algorithm.

Maximally probable is an ambiguous term when dealing with structured models. It could be taken to mean at least two distinct things. The MAP assignment $y_{MAP}$ of the hidden state sequence is the most probable joint assignment of states defined by Equation (5.5) and depicted in Figure 5.4a.

$$y_{MAP} = \arg \max_{y \in Y^T} p(y \,|\, x; \theta) \tag{5.5}$$

Another possible definition would be the *maximum marginal* (MM) assignment. It chooses the most probable hidden state for each word considering all possible assignments of states for the remaining words. The MM assignment $y_{MM}$ is defined by Equation (5.6). Figure 5.4c shows the marginal for one position and state.

$$y_{MM} = \arg \max_{y \in Y^T} \prod_{t=1}^{T} p(y_t, t \,|\, x; \theta) \tag{5.6}$$

As Merialdo (1994) and many others have noted, the MAP and MM assignments maximize different objectives. The MM assignment maximizes the accuracy of correct states per observations whereas the MAP assignment maximizes the number of completely correct state sequences. Both objectives are important from the point of view of POS tagging. However, they are often quite correlated and, at least in POS tagging, it does not matter in practice which of the criteria is used (Merialdo, 1994). Most systems, for example Church (1988), Brants (2000), Halácsy et al. (2007), have chosen to use MAP inference.

Although, MM inference is more rarely used with HMMs, computing the marginals is important both in unsupervised estimation of HMMs and discriminative estimation of sequence models. Therefore, an efficient algorithm for MM inference, the *forward*

*algorithm*, is presented below.

There are a number of strongly related algorithms for both exact MAP and MM inference. The work presented in this thesis, uses the Viterbi algorithm for MAP inference and the forward-backward algorithm for MM inference (Rabiner, 1989). *Belief propagation*, introduced by Pearl (1982), computes the MM assignment and can be modified to compute the MAP assignment as well. For sequence models, such as the HMM where hidden states form a directed sequence, belief propagation is very similar to the forward-backward algorithm. It can, however, be extended to cyclic graphs (Weiss, 2000) unlike the Viterbi algorithm.

Since cyclic models fall beyond the scope of this thesis and both the Viterbi and forward-backward algorithms are amenable to well known optimizations, which are of great practical importance, I will not discuss belief propagation belief propagation further. Koller and Friedman (2009) gives a nice treatment of belief propagation and graphical models at large.

Before introducing the Viterbi and forward-backward algorithm, it is necessary to investigate the forward algorithm, which is used to compute the marginal probability of an observation and also as part of the forward-backward algorithm. The forward algorithm and Viterbi algorithm are closely related.

### 5.3.1   The Forward Algorithm

Equations (5.5) and (5.6) reveal, that both MAP and MM inference require knowledge of the entire observation $x$. In the weather prediction example, observations are, however, always infinite. What kind of inference is possible in this case?

Even when we only know a prefix $x[1:t]$ (of length $t$) of the entire observation $x$, we can still compute the *belief state* (Boyen and Koller, 1998) of the HMM given the prefix. The belief state is in fact not a single state, but rather a distribution over the set of hidden states $Y$. It tells us how likely we are to be in state $z$ at time $t$, when we have emitted the prefix $x[1:t]$.

To compute the belief state at position $t$, we first need to compute the *forward probabilities* for each state $z \in Y$. The forward probability $\mathrm{fw}_{t,z}(x)$ of state $z$ at position $t$ is the probability of emitting prefix $x[1:t]$ and ending up in state $z \in Y$. For example, given an infinite observation $\{\text{☂}, \text{☂}, \text{☂}, ...\}$, the forward probability $\mathrm{fw}_{3,\text{RAIN}}$ is the probability that the third day is rainy, when the nurse carried an umbrella on the first and second days, but did not carry one on the third day.

Figure 5.4: foo.
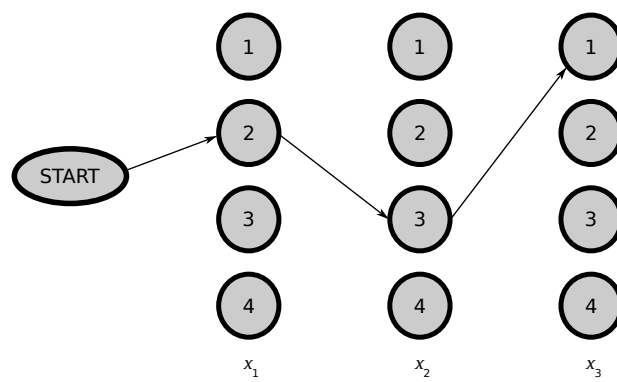


(a) Trellis and path.
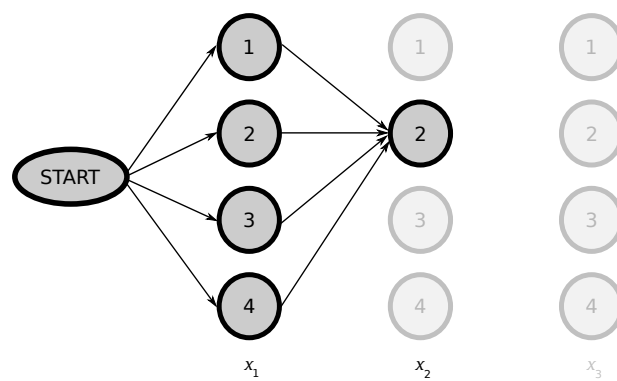


(b) Forward path prefixes.
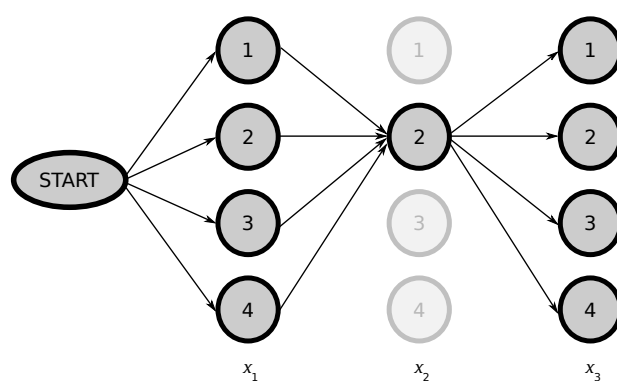


(c) Marginal paths.

I am going to make a technical but useful definition. The *prefix probability* of observation sequence $x = (x_1, ..., x_T)$ and state sequence $y = (y_1, ..., y_t)$ at position, where $t < T + 1$ is given by Equation (5.7).

$$p(x, \ y; \theta) = \left( \iota(y_1) \cdot \left( \prod_{u=1}^{t-1} \tau_{y_u}(y_{u+1}) \right) \cdot \prod_{u=1}^{t} \varepsilon_{y_u}(x_u) \right), \ t \leq T \qquad (5.7)$$

When $t = T$, this is very similar to the joint probability of $x$ and $y$, but the final transition is missing.

Conceptually, the forward probability is computed by summing over the probabilities of all path prefixes up to position $t$, where the state at position $t$ is $z$, see Figure 5.4b. Formally, the forward probability is defined by Equation (5.8).

$$\text{fw}_{t,z} = \sum_{y \in Y^t, \ y_t = z} p(x, \ y; \theta) \qquad (5.8)$$

Comparing Equations (5.8) and (5.1) shows that the forward probability in a sense represents the probability of a prefix of observation $x$.

The belief state and posterior marginal distribution may seem similar. They are, however, distinct distributions because the belief state disregards all information about observation $x$ after position $t$. In contrast, the marginal distribution encompasses information about the entire observation. For example the marginal probability of RAIN at position 3 is likely to depend strongly on whether or not Jill observes the nurse carry an umbrella on the fourth day. However, this will have no impact on the belief state.

Figure 5.5 demonstrates a naive approach to computing the forward probabilities. Simply list all relevant state sequences, compute the probability of each sequence and sum the probabilities. Unfortunately, the naive approach fails for large $t$ because the number of distinct state sequences depends on the sequence length in an exponential manner.

The complexity of the naive algorithm is $|Y|^t$, which is infeasible. For example, $f_{20,\text{RAIN}}(x)$ requires us to sum approximately 20 million probabilities and $f_{30,\text{RAIN}}(x)$ entails summation of approximately 540 million probabilities. Since observation sequences in domains such as natural language processing frequently reach lengths of $100$, a more efficient approach is required.

The belief state can be computed in linear time with regard to $t$ and quadratic time with regard to $|Y|$ using the *forward algorithm* (Rabiner, 1989), which is in fact simply a

Figure 5.5: foo

| $y_1$ | $y_2$ | $y_3$ | $p$ |
|---|---|---|---|
| CLEAR | CLEAR | CLEAR | $(0.75 \cdot 0.8 \cdot 0.9 \cdot 0.2) \cdot 0.9 \cdot 0.8 \approx 0.078$ |
| RAIN | CLEAR | CLEAR | $(0.25 \cdot 0.2 \cdot 0.3 \cdot 0.2) \cdot 0.9 \cdot 0.8 \approx 0.002$ |
| CLEAR | RAIN | CLEAR | $(0.75 \cdot 0.8 \cdot 0.1 \cdot 0.8) \cdot 0.3 \cdot 0.8 \approx 0.012$ |
| RAIN | RAIN | CLEAR | $(0.25 \cdot 0.2 \cdot 0.7 \cdot 0.8) \cdot 0.3 \cdot 0.8 \approx 0.007$ |
| | | | |
| ☂ | ☂ | ☔ | |
| | | | $\approx 0.098$ |

recursive application of the right distributive rule of algebra

$$a_1 \cdot b + ... + a_n \cdot b = (a_1 + ... + a_n) \cdot b$$

for real numbers $a_1$ up to $a_n$ and $b$.

Instead of computing the probability separately for each path, the forward probabilities for longer paths are computed incrementally using the forward probabilities of shorter paths. Examine Figure 5.5. By grouping rows one and two, as well as three and four into pairs, it is easy to see that

$$\mathrm{fw}_{3,\mathrm{CLEAR}} = (\mathrm{fw}_{2,\mathrm{RAIN}} \cdot \tau_{\mathrm{RAIN}}(\mathrm{CLEAR}) + \mathrm{fw}_{2,\mathrm{CLEAR}} \cdot \tau_{\mathrm{CLEAR}}(\mathrm{CLEAR})) \cdot \varepsilon_{\mathrm{CLEAR}}(☔)$$

Generalizing, we get the recursion in Equation (5.9).

$$\mathrm{fw}_{t,z} = \begin{cases} \iota(z) \cdot \varepsilon_z(x_1) & , t = 1 \\ \left( \displaystyle\sum_{z' \in Y} \mathrm{fw}_{t-1,z'} \cdot \tau_{z'}(z) \right) \cdot \varepsilon_z(x_t) & , 1 < t \leq T \\ \displaystyle\sum_{z' \in Y} \mathrm{fw}_{T,z'} \cdot \tau_{z'}(f) & , t = T+1,\ z = f. \end{cases} \tag{5.9}$$

The remaining forward probabilities $\mathrm{fw}_{T+1,z}$, where $z \neq f$ are defined to be $0$.

The forward probability $f_{T+1,f} = p(x; \theta)$. In fact one of the principal applications for the forward algorithm is computing the marginal probability of an observation. The other central application is in the forward-backward algorithm, which computes the state marginals.

The forward algorithm is outlined in Algorithm 5.1. Assuming that accessing the data structures x, i_prob, e_prob, tr_prob and trellis is constant time, the complexity of the algorithm is dominated by the three nested loops on lines 27–37. This shows that the complexity of the forward algorithm is linear with regard to the length of the sequence and quadratic with regard to the size of the hidden state set.

Although, the forward algorithm depends linearly on the observation length, its quadratic dependence on the size of the hidden state set is problematic from the perspective of morphological disambiguation of morphologically complex languages, where the size of the hidden state set is measured in the hundreds or thousands for regular HMMs. When using second order HMMs presented below, the state set can grow to tens of thousands or millions, which can slow down systems to a degree that makes them infeasible in practice. I will present partial solutions to these problems below.

## 5.3.2   The Viterbi Algorithm

Whereas the forward algorithm incrementally computes the marginal probability of an observation $x$, the Viterbi algorithm incrementally computes the MAP assignment for observation $x$.

A naive approach to finding the MAP assignment is to list all the hidden state paths, compute their probabilities and pick the one with the highest probability. Similarly as for the forward algorithm, the complexity of this approach is exponential with regard to the length of observation $x$.

Just as in the case of forward probabilities, the MAP assignment of hidden states for a prefix of the observation $x$ can be computed incrementally. Formally, the MAP assignment for a prefix $x[1 : t]$ is defined by equation (5.10) utilizing the joint prefix probability of $x$ and a state sequence $y$ of length $t$. Intuitively, it is the sequence of hidden states $y_{t,z}$ which maximizes the joint probability and ends at state $z$.

$$y_{t,z} = \underset{y \in Y^t, \ y_t = z}{\arg \max} \ p(x, \ y; \theta) \tag{5.10}$$

Comparing this equation with the definition of the forward probability $f_{t,z}$ in Equation 5.8, we can see that the only difference is that the sum has been changed to $\arg \max$.

I will now show that the MAP prefix $y_{t,z}$ can be computed incrementally in a similar fashion as the forward probability $f_{t,z}$. Suppose that $y_{t+1,z'} = (y_1, \ ..., \ y_t = z, \ y_{t+1} = z')$. I will show that $y_{t+1,z'}[1 : t] = y_{t,z}$. Let $y'$ be the concatenation of $y_{t,z}$ and $z'$. If

Algorithm 5.1: The forward algorithm in Python 3.

```python
 1  def forward(x, i_prob, e_prob, tr_prob):
 2      """
 3          x       - The observation as a list.
 4          i_prob  - Initial state distribution.
 5          e_prob  - Emission distributions.
 6          tr_prob - Transition distributions.
 7
 8          Return the trellis of forward probabilities.
 9      """
10
11      assert(not x.empty())
12
13      trellis = {}
14
15      # Indexing in python starts at 0.
16      x_1 = x[0]
17      T   = len(x) + 1
18
19      # Set final state F. States are consequtive integers
20      # in the range [0, F].
21      F = len(i_prob) - 1
22
23      # Initialize first trellis column.
24      for z in range(F):
25          trellis[(1,z)] = i_prob[z] * e_prob[z][x_1]
26
27      # Set all except the final column.
28      for t in range(2, T):
29          trellis[(t, z)] = 0
30
31          x_t = x[t - 1]
32
33          for z in range(F):
34              for s in range(F):
35                  trellis[(t, z)] = trellis[(t - 1, s)] * tr_prob[s][z]
36
37              trellis[(t, z)] *= em_prob[z][x_t]
38
39      # Set the last column.
40      for z in range(s_count):
41          trellis[(T + 1, z)] = trellis[(T, z)] * tr_prob[z][F]
42
43      return trellis
```

$y_{t+1,z'}[1:t] \neq y_{t,z}$, then

$$
\begin{aligned}
p(x,\ y_{t+1,z'}; \theta) &= p(x,\ y_{t+1,z'}[1:t]; \theta) \cdot \tau_z(z') \cdot \varepsilon_{z'}(x_{t+1}) \\
&< p(x,\ y_{t,z}; \theta) \cdot \tau_z(z') \cdot \varepsilon_{z'}(x_{t+1}) \\
&= p(x, y'; \theta)
\end{aligned}
$$

This contradicts the definition in Equation (5.10)[4].

We now get Equation (5.11), which gives us a recursion.

$$
y_{t+1,z} = \underset{z \in Y}{\arg\max}
\begin{cases}
\iota(z) \cdot \varepsilon_z(x_1) & , t = 1 \\
y_{t-1,z'} \cdot \tau_{z'}(z) \cdot \varepsilon_z(x_t) & , 1 < t \leq T \\
y_{T,z'} \cdot \tau_{z'}(f) & , t = T+1,\ z = f.
\end{cases}
\tag{5.11}
$$

### 5.3.3 Beam Search

As seen in the previous section, the complexity of the Viterbi algorithm depends on the square of the size of the hidden state set. This can be problematic when the set of hidden states is large, for example when the states represent POS tags in a very large label set or when they represent combinations of POS tags. When tagging, a morphologically complex language, the state set may easily encompass hundreds or even thousands of states.

*Beam search* is is a heuristic which prunes the search space explored by the Viterbi algorithm based on the following observation: in many practical applications, the number of hidden states which emit a given observation with appreciable probability is small. This is true even when the total number of hidden states is very large. For example, when the states represent POS labels, a given word such as "dog" can usually only be emitted by a couple of states (maybe Noun and Verb in this case).

When the Viterbi algorithm maximizes (5.11) for $y_{t+1,z}$, a large number of histories $y_{t,z}$ can, therefore, be ignored.

Often a constant number, the *beam width*, of potential histories are considered in the maximization. The complexity of the Viterbi algorithm with beam search is $o(|Y| \cdot \log|Y|)$. The log factor stems from the fact that the histories need to be sorted before maximization.[5]

---

[4]As long as we suppose that there is exactly one MAP prefix.

[5]Sequential decoding, an approximate inference algorithm, which was used for decoding before the Viterbi algorithm was in common use (Forney, 2005) is very similar to beam search. Indeed, it could be

In addition to histories, the possible hidden states for output can also be filtered. The simplest method in to use a so called tag dictionary. These techniques are described in Section 5.6.

### 5.3.4   The Forward-Backward Algorithm

The Viterbi algorithm computes the MAP assignment for the hidden states efficiently. For efficiently computing the marginal probability for a every state and position (see Figure 5.4c), the forward-backward algorithm is required.

Intuitively, the probability that a state sequence $y$ has state $z \in Y$ at position $t$, that is the probability that $y_t = z$ is the product of the probabilities that the prefix $y[1:t]$ ends up at state $z$ and the probability that the suffix $y[t:T]$ originates at $z$.

The name forward-backward algorithm stems from the fact, that the algorithm essentially consists of one pass of the forward algorithm, which computes prefix probabilities, and another pass of the forward algorithm starting at the end of the sentence and moving towards the beginning which computes suffix probabilities. Finally, the forward and suffix probabilities are combined to give the marginal probability of all paths where the state at position $t$ is $z$. These passes are called the forward and backward pass.

Formally, the suffix probabilities computed by the backward pass are defined by equation (5.12).

Since a backward pass of the forward algorithm carries the same complexity as the forward pass, we can see that the complexity of the forward-backward algorithm is the same as the complexity of the forward algorithm, however, there is a constant factor of two compared to the forward algorithm.

$$b_{t,z} = \begin{cases} \left( \sum_{z' \in Y} t_z(z') \cdot b_{t+1,z'} \right) \cdot e_z(x_{t+1}) & , 1 < t < T \\ t_z(f) & , t = T+1, \ z = f. \end{cases} \tag{5.12}$$

### 5.3.5   Sparse Forward-Backward Algorithms

FIXME (Pal et al., 2006).

---

said that Viterbi invented an exact inference algorithm, which is once more broken by beam search.

## 5.4   Estimation

HMMs can be trained in different ways depending on the quality of the available data, but also on the task at hand. The classical setting presented by Rabiner (1989) is nearly completely unsupervised: the HMM is trained exclusively from observations. Some supervision is nevertheless usually required to determine the number of hidden states[6]. Additionally priors on the emission and transitions distributions may be required to avoid undesirably even distributions (Cutting et al., 1992, Johnson, 2007).

The unsupervised training setting has two important and interrelated applications:

1. Modeling a complex stochastic process from limited data. Here the HMM can be contrasted to a Markov chain (Manning and Schütze, 1999, 318–320), where each emission can occur in a unique state leading to a higher degree of data sparsity and inability to model under-lying structure.

2. Uncovering structure in data, for example part-of-speech induction (Johnson, 2007).

The classical method for unsupervised Maximum likelihood estimation of HMMs is the *Baum-Welch algorithm* (Rabiner, 1989), which is an instance of the *expectation maximization algorithm* (EM) (Dempster et al., 1977) for HMMs.

In POS tagging and morphological disambiguation, the supervised training scenario is normally used. Supervised training consists of annotating a text corpus with POS labels and estimating the emission and transition probabilities from the annotated data.

Straight-forward counting is sufficient to get the ML estimates for the transition and emission distributions. For example, one can simply count how often a determiner is followed by a noun, an adjective or some other class. Similarly, one can count how many often a verb label emits "dog" and how often the noun label emits "dog".

Even in large training corpora, "dog" might very well never receive a verb label[7]. Nevertheless, "dog" can be a verb, for example in the sentence "Fans may dog Muschamp, but one thing's for certain: he did things the right way off the field.". To avoid this kind of problems caused by data sparsity, both emission and transition counts need to be smoothed.

---

[6]Although methods for determining the number of states from the data exist (**?**).

[7]There are ten occurrences of "dog" in the Penn Treebank and all of them are analyzed as nouns.

### 5.4.1 Counting for Supervised ML Estimation

When HMMs are used in linguistic labeling tasks, such as part-of-speech tagging, they are usually estimated in a supervised manner. Each label is thought to represent a hidden variable, and the HMM models the transitions from one label type to another and the emission of words from each label type.

```
Mr.          NNP
Vinken       NNP
is           VBZ
chairman     NN
of           IN
Elsevier     NNP
N.V.         NNP
,            ,
the          DT
Dutch        NNP
publishing   VBG
group        NN
.            .
```

Figure 5.6: foo

Figure 5.6 shows one sentence from the Penn Treebank (Marcus et al., 1993). The sentence is labeled with POS tags which are taken to be the hidden states of an HMM. When estimating an HMM tagger for the corpus, transitions probabilities, for example $t_{\text{NNP,VBZ}}$, and emission probabilities, for example $e_{\text{NNP}}(\texttt{Dutch})$ can in principle be computed directly from the corpus. For example the transition probability $t_{\text{NNP,VBZ}}$ and the emission probability $e_{\text{NNP}}(\texttt{Dutch})$ in the Penn Treebank are simply:

$$t_{\text{NNP,VBZ}} = \frac{\text{Count of POS tag pair } \texttt{NNP VBZ} \text{ in the corpus}}{\text{Count of POS tag } \texttt{NNP} \text{ in the corpus}} = \frac{4294}{114053} \approx 0.04$$

$$e_{\text{NNP}}(\texttt{Dutch}) = \frac{\text{Number of times } \texttt{Dutch} \text{ was tagged } \texttt{NNP} \text{ in the corpus}}{\text{Count of POS tag } \texttt{NNP} \text{ in the corpus}} = \frac{14}{114053} \approx 1.2 \cdot 10^{-4}$$

Simple computation of co-occurrences is insufficient because of data-sparsity. Words do not occur with all POS tags in the training corpus and all combpinations of POS tags are never observed. Sometimes this is not a problem. For example, "Dutch" could never

be a preposition. We know that the probability that a preposition state emits "Dutch" is $0$. However, there are at least three analyses that are perfectly plausible: noun (the Dutch language), adjective (property of being from The Nederlands) and proper noun (for example in the restaurant name "The Dutch").

Since "Dutch" occurs only 14 times in the Penn Treebank, it is not surprising that all of these analyses do not occur. Specifically, the noun analysis is missing. An HMM based on direct counts will therefore never analyze "Dutch" as a noun.

It is tempting to think that missing analyses are a minor problem because they only occur for relatively rare words such as "Dutch". Unfortunately, a large portion of text is made up from rare words. The problem therefore has very real consequences.

The usual approach is to use a family of techniques called *smoothing*. In smoohing, zero counts and all other counts are modified slightly to counter-act aprsity.

Smoothing of emission proabilities and transition probabilities differ slightly. For transition probabilities it is common practice to use counts of both tag pairs and single tags to estimate tag probabilities either in a back-off scheme (**?**) or using interpolation (Brants, 2000). Many sophisticated interpolation schemes can be used for example Kneser-Ney (**?**).

Many systems such as the HMM tagger by Brants (2000) do not smooth emission probabilities for words seen in the training corpus. However, words *not* seen in the training corpus, or out-of-vocabulary (OOV) words still require special processing. The simplest method is to estimate combined statistics for all words occurring one time in the training corpus and use these statistics for OOV words (**?**). Lidstone smoothing is another similar approach (**?**). Another approach would be to build models to guess the analysis of OOV words using the longest suffix of the word shared with a word in the training data.

Brants (2000) employs a specialized emission model for OOV words, which combines both approaches. It assigns a probability $p(y|x)$ for any label $y \in \mathcal{Y}$ and an arbitrary word $x$ based on suffixes $s_i$ of the word different lengths. The subscript $i$ indicates suffix length.

The model uses relative frequencies $\hat{p}(y|s_i)$ of label $y$ given each suffix $s_i$ of $x$ that occurs in the training data. The frequencies for different suffix lengths are recursively combined into probability estimates $p(y|s_i)$ using successive interpolations

$$p(y|s_{i+1}) = \frac{\hat{p}(y|s_{i+1}) + \theta \cdot p(y|s_i)}{1 + \theta}.$$

The base case $p(y|s_0)$, for the empty suffix $s_0$, is given by the overall frequency of label type $y$ in the training data, i.e. $p(y|s_0) = \hat{p}(y)$, and the interpolation coefficient $\theta$ is the

variance of the frequencies of label types in the training data

$$\theta = \frac{1}{|\mathcal{Y}|-1} \sum_{y \in \mathcal{Y}} (\hat{p} - \hat{p}(y))^2.$$

Here $\hat{p}$ is the average frequency of a label type. Finally, $p(y|x) = p(y|s_I)$, where $s_I$ is the longest suffix of $x$ that occurs in the training data. However, a maximal suffix length is imposed to avoid over-fitting. Brants (2000) uses $10$ for English. Moreover, the training data for the emission model is restricted to include only "rare" words, that is words whose frequency does not exceed a given threshold. This is necessary, because the distribution labels for OOV words usually differs significantly from the overall label distribution in the training data.

Brants (2000) does not discuss the choice of $\theta$ in great length. It is, however, instructive to consider the effect of the magnitude of $\theta$ on the emission model. When the variance of label type frequencies, that is $\theta$, is great, shorter suffixes and the prior distribution of label types will weigh more than long suffixes. This is sensible as (1) a high $\theta$ implies that the distribution of words into label types is eschewed a priori and (2) long suffix statistics are sparse and thus prone to overfitting. When $\theta$ is low, the prior distribution of word classes is closer to the even distribution. Therefore, there is no choice but to trust longer suffixes more.

For morphologically complex languages, the smoothing scheme employed by Brants (2000) may be inferior to a longest suffix approach utilized by Silfverberg and Lindén (2011) and Lindén (2009). This may happen because productive compounding. For languages with writing systems that radically differ from English, such as Mandarin Chinese, suffix based methods work poorly. Other methods, such as basing the guess on all symbols in the word, may work better. Huang et al. (2007) smooth symbol emission probabilities using geometric mean.

### 5.4.2   The EM algorithm for Unsupervised ML Estimation

The Baum-Welch, or Expectation Maximization, algorithm for HMMs is an iterative hill-climbing algorithm, that can be used to find locally optimal parameters for an HMM given a number of unlabeled independent training examples which are drawn from the distribution that is being modeled by the HMM. Here is a short outline of the algorithm:

1. Random initialize the emission and transition parameters.

2. Use the forward-backward algorithm to compute posterior marginals over input positions.

3. Use the posterior marginals as *soft counts* to estimate new parameters.

4. Repeat steps 2 and 3 until the improvement of likelihood of the training data is below a threshold value.

In step 2, the algorithm computes the maximally likely state distribution for each position given the current parameters. In step 3, the state distributions for each position in the input data are used to infer the MAP parameters for the HMM. Therefore, the marginal probability of the training data has to increase on every iteration of steps 2 and 3, or possible remain the same, if the current parameters are optimal.

There are no guarantees that the optimum found by the EM algorithm is global. Therefore, several random restarts are used and parameters giving the best marginal probability for the training data are used.

A more formal treatment of the EM algorithm can be found in Bilmes (1997).

## 5.5   Model Order

The standard HMM presented above is called a *first order model* because the next hidden state is determined solely based on the current hidden state. This model is easy to estimate and resistant to over-fitting caused by data-sparsity, but it fails to capture some key properties of language. For example, in the Penn Treebank, the probability of seeing a second adverb RB following and adverb is approximately, 0.08. If the first order assumption were valid, the probability of seeing a third adverb following two adverbs should also be 8%, however it is lower, around 5%.
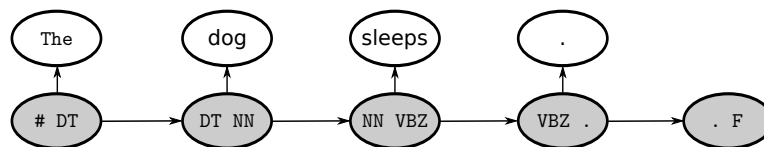


Figure 5.7: foo

The example with adverbs is poor at best, but it illustrates the kind of effect *second order* information can have. Second order HMMs are models where transitions are conditioned on two preceding hidden states. Equivalently, in POS tagging, the hidden states

can be taken to be pairs of POS tags, e.g. `DT, NN`. In such a model transitions can only occur to a subset of the hidden state set. For example a transition from `DT, NN` to `NN, VBZ` is possible, but a transition to `JJ, NN` is impossible. Figure 5.7 illustrates a path with legal transitions.

Figure 5.7 implies that emissions in a second order model are conditioned on two labels like the transitions. However, many existing HMM based POS tagging systems such as Brants (2000) condition emissions only on one label, that is use $e_{t_i,t_{i-1}}(w_i) = p(w_i \,|\, t_i)$ instead of $e_{t_i,t_{i-1}}(w_i) = p(w_i \,|\, t_{i-1},\ t_i)$. The reason is probably data-sparsity. Therefore, these systems cannot be called HMMs in the strictest sense of the word. They are instead called trigram taggers.

Halácsy et al. (2007), show that it is possible to maintain the correct HMM formulation over-come the data sparseness problem and achieve gains over the more commonly used trigram tagger. However, they fail to describe the smoothing scheme used, which is crucial. This defect is partly remedied by the fact that the system is open-source. One of the chief contributions of Silfverberg and Lindén (2011) was to investigate the effect of different ways of estimating the emission parameters in a generative trigram tagger paying attention to smoothing.

Increasing model order unfortunately leads to increased data sparsity, because the number of hidden states increases. Therefore, smoothing transition probabilities is even more important than in the first order case. Even using smoothing, third and higher order models tend to generalize to unseen data more poorly than lower order models because of over-fitting (**?**).

An alternative to increasing model order, is to use so called latent annotations (Huang et al., 2009) in an otherwise regular first order HMM. Conceptually, each label for example `NN` is split into a number of sub-states `NN1`, `NN2` and so on. Expectation maximization is used to train the model in a partly supervised fashion. Splitting labels, and indeed any increase in order, is probably works better for label sets with quite few labels. Otherwise, it will simply contribute data sparsity.

## 5.6   HMM taggers and Morphological Analyzers

The inventory of POS labels that are possible for a given word form tends to be small. For example the English "dog" can get two of the Penn Treebank POS tags singular noun `NN` and `VB` infinitive verb form. The remaining 43 POS tags can never label "dog". Con-

sequently, in an HMM POS tagger, only the states corresponding to VB and NN should ever emit the word "dog".

A tag dictionary (Brants, 2000) can be used in combination with the Viterbi algorithm to limit the set of hidden states that could emit a word. The tag dictionary can be constructed from the training corpus. Additionally, an external lexical resource, such as a morphological analyzer, can be used. Such a lexical resource can help to compensate for missing statistics for OOV words. In the frequent setting, where most rare words have quite few analyses, this can have a substantial effect on tagging accuracy.

## 5.7 Enriching the emission and transition models

- Halácsy et al. (2007) and Silfverberg and Lindén (2011).

## 5.8 Problems

In the standard first order HMM an observation depends only on the current hidden state. If the hidden state is given, the observation cannot be influenced by the hidden states at other positions in the input or the other observations. This facilitates estimation and makes the system resistant to over-fitting, but at the same time it severly limits the set phenomena tht the model can capture.

An example from POS tagging the Penn Treebank illustrates this problem. The Penn Treebank has two labels for common nouns: NN for singular nouns and NNS for plural nouns.

- Local normalization.

- Inability to use word context.

- Label bias.

- The inability to use rich features, causes problems in domains other than POS tagging and in POS tagging for MR languages.

- Smoothing is difficult.

- Differences in performance between generative HMMs and discriminative approaches are even greater for morphologically complex languages and small training sets.

- OOV words may require different mechanisms depending on language again causing problems for MR lanuages.

## 5.8.1 Summary

A SUMMARY

# Chapter 6

# Conditional Random Fields

## 6.1 Discriminative modeling

As seen in Chapter 5, the HMM POS tagger can be viewed as a state machine which alternates between sampling observations, that is words, from a state specific observation distributions, and sampling successor states, that is the morphological labels, from state specific transition distributions. Each emission and each successor state is conditioned *solely* on the current state. These independence assumptions are harsh. For example the Finnish cannot be adequately modeled, because the model does not include direct information about neighboring words in a sentence.

Although information about for example word collocations and orthography is quite useful in morphological labeling, it is often difficult to incorporate more elaborate contextual information in a generative model. As Sutton and McCallum (2012) note, there are two principal methods of doing this are improving the emissions model, which may be intractable because the model needs to account for complex dependencies between words in a sentence and their orthographic features, and replacing the usual emission model with for example a Naive Bayes' model.

In a domain closely related to morphological labeling, namely biomedical entity extraction,Ruokolainen and Silfverberg (2013) show that the Naive Bayes approach fails. In fact, adding richer context modeling such as adjacent words, worsens the performance of the modeling. One reason for this may be that overlapping information sources tend to cause the Naive Bayes model to give overly confident probability estimates (Sutton and McCallum, 2012). Combining them in a structured manner can therefore be problematic.

In contrast to generative sequence models, discriminative sequence models such as

Maximum Entropy Markov Models (Ratnaparkhi, 1998) and Conditional Random Fields (Lafferty et al., 2001) can incorporate overlapping sources of information. They model the conditional distribution of label sequences $p(y \mid x)$ directly instead of modeling the joint distribution $p(x, y)$. Therefore, they do not need to model the distribution of sentences at all.

Discriminative models assign probabilities $p(y \mid x)$ for label sequences $y$ and word sequences $x$ by extracting local features from the input sentence and label sequence. Examples of local features include $x_t$ *is "dog" and* $y_t$ *is "NN"* and $y_{t-1}$ *is "DT" and* $y_t$ *is "NN"*. Each feature is associated with a parameter value and the parameter values are combined to give the conditional likelihood of the entire label sequence. Naturally, the label sequence which maximizes the conditional likelihood given sentence $x$ is the label sequence returned by the discriminative POS tagger.

In generative models, emissions and transitions are independent. Both are determined exclusively based on the current label. Contrastingly, in discriminative models, there are no emissions or transitions. Instead, it is customary to speak about unstructured features relating exclusively to the input sentence, and structured features, which incorporate information about the label sequence. Simplifying a bit, discriminative models make no independence assumptions among features relating to a single position in the sentence. This allows for improved fit to training data but parameter estimation becomes more complex as we shall soon see. Moreover, discriminative models are more prone to over-fitting. This is of course the famous bias-variance trade-off (Geman et al., 1992).

## 6.2   Maximum Entropy Modeling

### 6.2.1   Example

## 6.3   Basics

I will now describe a CRF POS tagger from a practical point-of-view. The tagging procedure encompasses two stages: feature extraction and inference using an exact or approximate inference algorithm. Whereas inference in CRFs is very similar to inference in HMMs, we did not discuss feature extraction in association to HMMs. This is because HMM taggers use a restricted set of features (the current word and preceding labels).

| $y$ | DT | NN | VBZ | . |
|-----|-----|-----|-----|---|
| $x$ | The | dog | eats | . |

Features are true logical propositions, which connect aspects of the input sentence with labels or parts of the label sequence. Given sentence $x$ and label sequence $y$ of length $n$, we extract features at every position $t$ in the sentence. For example at position $2$ in sentence $x$, we could extract *The current word $x_t$ is "dog" and the label is "NN"* and *The previous label is "DT" and the current label is "NN"*. We could, however, not extract the same feature *The current word is "dog" and the label is "NN"* at position $1$, because this proposition is false when $t = 1$ (the word at position 1 is "The" and the label is "VBZ").

Features are conjunctions of two parts: a feature template, for example *The current word is "dog"* and a label *the label is "NN"*. The set of features recognized by a CRF POS tagger contains all conjunctions $f \& y$ of feature templates $f$ present in the training data and labels $y$. For example, the tagger would know *The current word is "dog" and the label is "DT"* although it is unlikely that this feature would ever be observed in actual training data.

Ratnaparkhi (1996) introduced a rather rudimentary feature set and variations of this feature set are commonly used in the literature (for example Collins (2002) and Lafferty et al. (2001)). Let $W$ be the set of word forms in the training data. Additionally let $P$ and $S$ be the sets of prefixes and suffixes of maximal length $4$ of all words $w \in W$. Then, the Ratnaparkhi feature set contains the unstructured feature templates in Table 6.1 and the structured feature templates in Table 6.2.

These feature templates are then combined with all labels occurring in the training set. It is instructive to try to estimate the number of features when using a realistic training set of size around a million words. The number of features is be $O(\max(|Y|^2, |W|) \cdot |Y|)$. For small label sets and large training data, the bulk of the feature set tends to consist of unstructured features. However, for large label sets in the order of $1,000$ labels, there will be a significant number of structured features (one billion in this case). This necessitates either dropping second order structured features or using sparse feature representations. All structured features simply cannot be represented in memory. We will see techniques to circumvent these problems. Especially the averaged perceptron is essential.

It is common to represent the CRF using linear algebra. Each position $t$ in the sentence is represented as a vector $\phi_t$ whose dimensions correspond to the entire space of possible features. The selection of features is finite because it is limited by the training data. There

| Feature template | Example |
| --- | --- |
| The current word is $w$ | The current word is "dog" |
| The current word has prefix $p$ | The current word has prefix "d-" |
| The current word has suffix $s$ | The current word has suffix "-og" |
| The current word contains a digit | |
| The current word contains a hyphen | |
| The current word contains a upper case letter | |
| The previous word is $w$ | The previous word is "The". |
| The next word is $w$ | The next word is "eats". |
| The word before the previous word is $w$ | |
| The word after the next word is $w$ | |

Table 6.1: foo

| Feature template | Example |
| --- | --- |
| The label of the previous word is $y$ | The label of the previous word is "NN". |
| The label of the previous two words are $y'$ and $y$ | The labels of the two previous words are "DT" and "NN". |

Table 6.2: foo

are only finitely many word forms, suffixes, morphological labels and so on in the training data. The elements of each vector $\phi_t$ represent activations of features. In the present work all elements are either $0$ or $1$ mirroring false and true truth values, but other activations in $\mathbb{R}$ can also be used, if the truth values of the feature propositions exist on a non-binary scale.

In order to represent sentence positions as vectors, we need an injective index function $I$ which maps features onto consecutive integers starting at 1. For each feature $f$, $I(f)$ will be an element in $\phi_t$. In a concrete implementations, the index function $I$ could be implemented as a hash function.

Given a sentence $x$ and label sequence $y$, we can extract the set of features $F_t(x)$ for each position $t$ in $x$. Let $\phi_t \in \mathbb{R}^N$ be a vector defined by

$$\phi_t(i) = 1, \ \text{ if } i \leq N \text{ and } I(f) = i \text{ for some } f \in F_t$$

all other entries in $\phi_t$ are $0$.

Given a parameter vector $\omega \in \mathbb{R}^N$, the probability $p(y|x)$ is

$$p(y|x) \propto \prod_{t=1}^{T} \exp(\omega^\top \phi_t)$$

Specifically, the same parameter vector $\omega$ is shared by all sentence positions and the probability $p(y|x)$ is a log linear combination of parameter values in $\omega$.

Lafferty et al. (2001)

## 6.4   Logistic Regression

The simplest Conditional Random Field is the *Logistic Regression Model* (LRM). It is an unstructured probabilistic discriminative model. In this section, I will present a formal treatment of the LRM because it aids in understanding more general CRFs.

### 6.4.1   The Model

Regular linear regression models a *real valued quantity* $y$ based on independent variables $x_1, ..., x_n$. In contrast the LRM is a regression model which models *the probability* that an observation $x$ belongs to a class $y$ in a finite class set $Y$. For example, the logistic classifier can be used to model the probability of a tumor belonging to the class MALIGNANT or BENIGN. The probability is based on quantifiable information about the tumor such as its size, shape and the degrees of expression of different genes in the tumor cells. These quantifiable information sources are the *feature templates* of the logistic classifier and combined with class labels they make up the features of the model.

The material at hand deals with linguistic data where most information sources are binary, for example whether a word ends in suffix "-s" and whether a word is preceded by the word "an". In other domains such as medical diagnostics, more general features can be used. These can be real valued numerical measurements such as the diameter of a tumor. This treatment of logistic classifiers will focus on the binary valued case. When using binary features, we can equate the example $x$ with the set of feature templates $F_x \subset F$ that it *activates*, that is *Tumor diameter $\geq$ 5 cm, Preceded by "an"* and so on. Examples that activate the exactly same feature templates will be indistinguishable from the point of view of the Logistic Regression model.

The logistic classifier associates each combination of a feature template and class with a unique feature and a corresponding real valued parameter. Intuitively, the logistic

classifier models correlations of feature templates and classes by changing the parameter values of the associated features. For example, it might associate the feature template *Tumor diameter ≥ 5 cm* more strongly with the class MALIGNANT than the class BENIGN if large tumors are cancerous more often than smaller ones. This could be reflected in the parameter values of the model that correspond to the features $f$ = *Tumor diameter ≥ 5 cm and class is MALIGNANT* and $f'$ = *Tumor diameter ≥ 5 cm and class is BENIGN* so that the parameter value for $f$ is greater than the parameter value for $f'$. In general parameter values, however, also depend on other features and feature correlations in the model. Therefore we can say that the parameter value of, $f$ will be guaranteed to be greater than the parameter value of $f'$ when $f$ is the sole feature template and the model accurately reflects the original distribution of class labels among examples. In the general case, where there are several feature templates, this might fail to hold.

Formalizing the notation used in Section 6.3, let $F$ be a finite set of feature templates and $Y$ a finite set of classes. Each combination of feature template $f \in F$ and class $y \in Y$ corresponds to a unique feature. Therefore, the model will have $|F \times Y|$ features in total. Let $\theta$ be a real valued parameter vector in $\mathbb{R}^{|F \times Y|}$ and let I be a 1-to-1 index function which maps each combination of feature template and class onto the indexes of $\theta$, that is $1 \leq \mathrm{I}(f, y) \leq |F \times Y|$.

For each example $x$, let $F_x$ be the set of feature templates that $x$ activates and let $y \in Y$ be a class. Then the feature vector associated with $x$ and $y$ is $\phi(x, y) = \{0, 1\}^{|F \times Y|}$ defined by

$$\phi(x, y)[i] = \begin{cases} 1 & \text{iff } i = \mathrm{I}(f, y) \text{ for some } f \in F_x, \\ 0 & \text{otherwise.} \end{cases}$$

Now the conditional probability $p(y \,|\, x)$ defining the Logistic classifier is given by Equation (6.1). The equation defines a probability distribution over the set of classes $Y$ because each quantity $p(y \,|\, x; \theta)$ is a positive real and the quantities sum to 1.

$$p(y \,|\, x; \theta) = \frac{\exp(\theta^\top \phi(x, y))}{\sum_{z \in Y} \exp(\theta^\top \phi(x, z))} \tag{6.1}$$

Often a special bias term is used in Equation 6.1. It is

The Logistic Regression Model is log-linear as demonstrated by Equation 6.2, which represents the model using a cost function.

$$-\log p(y \mid x; \theta) = log(\mathrm{Z}(x; \theta)) - \theta^\top F_y(x), \text{ where } Z(x; \theta) = \sum_{z \in Y} \exp(\theta^\top F_z(x)) \quad (6.2)$$

Given labeled training data $\mathcal{D} = \{(x_1, \ y_1), \ ..., \ (x_n, \ y_n)\}$, there exist several options for estimating the parameters $\theta$. The most commonly used is the maximum likelihood, or equivalently minimum cost, estimation. The minimum cost estimate for the parameters $\theta$ using $\mathcal{D}$ is given by equation (6.3), where $\mathrm{Z}(\mathcal{D}; \theta) = \sum_{(x, \ y) \in \mathcal{D}} \mathrm{Z}(x; \theta)$ is the partition function of the entire data set $\mathcal{D}$.

$$\theta = \arg\min_{\theta'} \Big( \log(\mathrm{Z}(\mathcal{D}; \theta)) - \sum_{(x, \ y) \in \mathcal{D}} \theta'^\top F_y(x) \Big) \quad (6.3)$$

The probability $p(y \mid x; \theta)$ has exponential form, which means that the probability is proportional to a product of factors of the form $e^{ap}$, where $a$ is an activation (0 or 1) and $p$ is a parameter. This has three significant consequences:

1. The function $\theta \mapsto p(y \mid x; \theta)$ is smooth,

2. it is convex,

3. there exists a *unique* $\theta$ maximizing the likelihood of the training data $\mathcal{D}$, and

4. the model $p(y \mid x; \theta)$ is maximally unbiased.

Smoothness follows from the fact that each factor $a \mapsto e^{ap}$ is smooth and products and sums of smooth functions are smooth. Convexity of the likelihood follows by a straightforward application of the Hölder inequality . Property 3 is a consequence of properties 1 and 2 and Property 4 follows from the discussion in Section 6.2.

The log-linear form of the logistic classifier is motivated by the concept of maximum entropy, which was introduced in Subsection 6.2.1.

Although the maximization in Equation 6.1 cannot be solved for exactly in general, the convexity and smoothness of $p(y \mid x; \theta)$ mean that efficient numerical methods can be used for approximating the maximum to an arbitrary precision.

## 6.5   The Logistic Regression Model as a Classifier

Inference for a Logistic Regression Model means finding the probability of each class label $y \in Y$ given example $x$. The full computation of the probability is, however, not

needed when the model is used as a classifier. For simply finding the class $y_{max}$ which maximizes the conditional likelihood in equation 6.4 given fixed parameters $\theta$ it is sufficient to maximize the numerator of $p(y \mid x; \theta)$.

$$y_{max} = \arg\max_{y \in Y} p(y \mid x; \theta) = \arg\max_{y \in Y} \frac{\exp(\theta^\top \phi(x, y))}{Z(x; \theta)} = \arg\max_{y \in Y} \exp(\theta^\top \phi(x, y)) \tag{6.4}$$

To avoid underflow when using finite precision real numbers (such as floating-point numbers), the maximization is usually rephrased as the minimization of a cost-function in Equation 6.5

$$y_{max} = \arg\min_{y \in Y} \theta^\top \phi(x, y) \tag{6.5}$$

From a practical implementation perspective, the minimization in Equation 6.5 boils down to computing one inner product $\theta^\top \phi(x, y)$ for each label $y \in Y$ and finding the minimum. Using a suitable sparse approach each of the inner products can be computed in $O(|F_x|)$ time, where $F_x$ is the set of feature templates activated by example $x$. Therefore, the worst-case complexity of classification is dependent on the size of the label set $Y$ and the number of feature templates $f \in F$, that is the complexity is $O(|Y||F|)$.

## 6.6 Estimation

As seen in Section **??**, the Logistic Regression Model is smooth, that is the likelihood $p(y_1 \mid x_1; \theta)...p(y_n \mid x_n; \theta)$ of a labeled training data set $\mathcal{D} = \{(x_1, y_1), ..., (x_n, y_n)\}$ is a smooth function of the parameter vector $\theta$. This allows formulation of the parameter estimation task for the Logistic Regression Model as a optimization task whose solution can be approximated using numerical techniques.

## 6.7 CRF – A Structured Logistic Classifier

## 6.8 Note on Terminology

- The term perceptron tagger is commonly found in the litterature, e.g. Collins (2002).

- The model is called a CRF.

• The estimator can be a ML, Perceptron, pseudo likelihood, pseudo perceptron...

## 6.9   Inference

• Inference using Viterbi.

## 6.10   Estimation

• Iterative process: label data, adjust parameters and repeat.

• Use SGD or L-BFGS (Vishwanathan et al., 2006) for ML estimation.

• Use averaged perceptron (Collins, 2002).

• Dev data for adjusting hyper parameters: number of iterations and regularization hyper-parameters, model order.

• Problems with exact estimation.

• Layered CRF Mueller et al. (2013), Weiss and Taskar (2010) and Charniak and Johnson (2005).

## 6.11   Approximate Estimation

• Beam search.

• Violation fixing.

• Label guessing.

## 6.12   CRF taggers and Morphological Analyzers

## 6.13   Enriching the Structured Model

• Utilizing sub-label structure.

# Chapter 7

# Lemmatization

## 7.1 Introduction

## 7.2 Data-Driven Lemmatization

- Classifier based: Grzegorz Chrupala and van Genabith (2008).

- Finite-state based: Lindén (2009).

- Combination: Hulden et al. (2014).

## 7.3 Combining Morphological Analyzers and Data-Driven Lemmatization

# Chapter 8

# Conclusions

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# Contributions

# Articles

# Combining Statistical Models for POS Tagging using Finite-State Calculus

**Miikka Silfverberg**
Helsinki University
Helsinki, Finland
miikka.silfverberg@helsinki.fi

**Krister Lindén**
Helsinki University
Helsinki, Finland
krister.linden@helsinki.fi

## Abstract

We introduce a framework for POS tagging which can incorporate a variety of different information sources such as statistical models and hand-written rules. The information sources are compiled into a set of weighted finite-state transducers and tagging is accomplished using weighted finite-state algorithms. Our aim is to develop a fast and flexible way for trying out different tagger designs and combining them into hybrid systems. We test the applicability of the framework by constructing HMM taggers with augmented lexical models for English and Finnish. We compare our taggers with two existing statistical taggers TnT and Hunpos and find that we achieve superior accuracy.

## 1 Introduction

Part-of-Speech (POS) tagging, and other sequential labeling tasks like named entity recognition and chunking, constitute core tasks of language technology. Highly successful POS taggers for English have been constructed both using rule-based methods e.g. finite-state constraints used by Voutilainen (1995) and statistical methods e.g. Hidden Markov Models (HMM) used by Brants (2000).

Besides HMMs, other statistical models such as Conditional Random Fields and Maximum Entropy Models have recently been used to construct POS taggers, but HMMs remain one of the most widely used in practice. Though the more recent models surpass HMMs in accuracy, the great tagging speed and a fast development cycle of HMMs ensure a continuing popularity.

Accuracies for state of the art statistical taggers for English newspaper text surpass 97%, but results for applying these models on other languages are not always as encouraging. E.g. Dredze and Wallenberg (2008) report an accuracy 92.06% on tagging Icelandic using bidirectional sequence classification.

Low accuracy is partly due to the lack of sufficiently large tagged corpora, which can be used as training material. Reduction of accuracy can also result from the fact that the syntax and morphology of many languages differ substantially from English syntax and morphology. E.g. many languages do not have as rigid word order as English and many languages incorporate far more extensive morphological phenomena. Thus models, which have been developed for English, may not work well on many other languages.

These practical and theoretical problems associated with constructing POS taggers for virtually all of the world's languages, demonstrate the need for POS tagging models, which can incorporate a variety of different information sources including different kinds of statistical models but also more linguistic models like the ones utilized by Voutilainen (1995). Ideally the linguistic models could be used to fine-tune the result of the statistical tagging.

We propose a general framework for building POS taggers, where various kinds of statistical models and other POS tagging models can be combined using weighted finite-state calculus. Using this framework, developers can test a variety of models for tagging a language and apply the models in parallel. E.g. a statistical model trained with insufficient training data can be augmented with hand-made or machine-learned rules for common tagging errors.

In order to test the framework, we trained standard second order HMMs for Finnish and English and augmented these with extended lexical models using tag context.

We train and evaluate the English tagger using the Wall Street Journal (WSJ) corpus from Penn

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Treebank II (Marcus et al., 1994). We compare the accuracy obtained by our model with the well known and widely used HMM tagger TnT (Brants, 2000) and a more recent open-source HMM tagger Hunpos (Halácsy et al., 2007), which also utilizes an extended lexical model. After improving upon the lexical model of Hunpos, our tagger obtains an accuracy of 96.67%, outperforming both TnT (96.46%) and Hunpos (96.58%).

For training and testing the Finnish tagger, we use morphologically analyzed and disambiguated newspaper text. The optimization of the model for Finnish requires some changes in the model. Together these changes improve the accuracy from a baseline second order HMM by more than 1%. We also train a Hunpos tagger for Finnish and compare it with our own tagger. The 96.02% accuracy, we obtain on the Finnish material, clearly outperforms Hunpos (95.62%).

We implemented all taggers using the freely available HFST-interface for weighted finite-state transducers (Lindén et al., 2009). An open-source interface for constructing taggers in our framework will be made publicly available.

This paper is structured in the following way. We first review some earlier work on enhancing the accuracy of HMMs. We then introduce our framework for constructing taggers in section 4. In section 5 we introduce an HMM tagger augmented with contextual lexical probabilities, which we implemented for English and Finnish in our framework. We then evaluate the English and Finnish taggers using corpus data and compare them with TnT and Hunpos. Following evaluation, we present a brief discussion on our results and future work. Finally we conclude the paper.

## 2  Previous Work

Statistical POS tagging is a common task in natural language applications. POS taggers can be implemented using a variety of statistical models including Hidden Markov Models (HMM) (Church, 1999; Brants, 2000), Maximum Entropy Models (Tsuruoka et al., 2005) and Conditional Random Fields (Lafferty et al., 2001).

HMMs are probably the most widely used technique for POS tagging and one of the best known implementations of an HMM is TnT by Brants (2000). When tagging the WSJ corpus using the splits introduced by Collins (2000), TnT achieves an accuracy of 96.46%. Although more recent

statistical techniques result in improved accuracy, HMMs have remained in use chiefly because of the speed of both developing a tagger and tagging.

Recently Banko and Moore (2004) and Halácsy et al. (2007) have worked on improving the accuracy of HMMs by adding tag context into the lexical model of the HMM. The technique was pioneered by Toutanova et al. (2003) in the context of Conditional Markov Models.

The strength of Banko and Moore (2004) is that their lexical models use both left and right context when determining the conditional probability which should be associated to a wordform given a tag. The Hunpos tagger by Halácsy et al. (2007) uses only the left tag context, but it does not require a full lexicon, which makes it very practical.

We combine the left and right tag context in lexical models with a guesser for unknown wordforms. Our approach differs from Hunpos in that we only use contextually dependent lexical probabilities for known words.

Besides evaluating our approach to POS tagging by constructing a tagger for English text, we also test our approach on Finnish. Work with statistical POS tagging for Finnish seems to be virtually non-existent. Silfverberg and Lindén (2010) derive a Finnish POS tagger for the Finnish Europarl corpus (Koehn, 2005), which achieves high accuracy i.e. 96.63%, but these results could be contested on the grounds that the Europarl corpus is translated into Finnish from other languages. Silfverberg and Lindén (2010) also use an extremely large (25 million tokens) corpus. We use Finnish newspaper text to train and evaluate the tagger. Our training corpus is comparable in size to the Wall Street Journal corpus.

## 3  Note on Terminology

We use the terms *analysis*, *POS tag* and *tag* interchangeably to refer to POS tags, which are given for words. The *correct tag* or *analysis* refers to the intended analysis of a word in a gold standard corpus. By the term an *analysis of a sentence*, we signify one possible way to assign a unique POS tag to each of the words in the sentence. We use the term *correct analysis of a sentence* to denote the unique analysis where all of the words receive their correct analyses.

The term *analysis or tag profile of a word* refers to the set of tags which can occur as its POS analyses.

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If all of the analyses of a sentence are compiled into a transducer, the paths of the transducer correspond exactly to the analyses of the sentence. In this setting, we use the terms analysis and path interchangeably. We call the transducer, compiled from the tag profiles and associated probabilities, the *sentence transducer*.

## 4    A Framework for Constructing POS Taggers

Our framework factors POS tagging into two tasks: (i) assigning tag profiles and probabilities $p(w|t)$ to each word $w$ in a sentence and each of its possible analyses $t$ and (ii) re-scoring the different analyses of the entire sentence using parallel weighted models for word and tag sequences.[1]

In the first task, the tag profile for a word $w$ and the probabilities $p(w|t)$ for each of its tags is estimated from a training corpus. The probabilities are independent of surrounding words and tags. For unknown words $u$, a number of guessers can be included. These estimate the probabilities $p(u|t)$ using the probabilities $p(s|t)$ for the suffixes of $u$. The suffix probabilities can be estimated from a training corpus.

A number of guessers can be used to estimate the distribution of analyses for different kinds of unknown words. Like Hunpos and TnT, we always include different guessers for upper case words and lower case words, which improves accuracy.

The tag profiles of words along with tag probabilities are compiled into a weighted finite-state transducer, which associates a probability for every possible analysis of the sentence. The probability assigned to a path at this stage is the product of lexical probabilities.

After assigning tag profiles and probabilities for words, the second task is to re-score the paths of the sentence transducer. Different models can be used to accomplish this. Each of the models adds some weight to each of the analyses of the sentence and their combined effect determines the best path i.e. the most probable path. We could also incorporate models which forbid some analyses. This means that the analyses are discarded in favor of other analyses which initially seemed less

likely. Such models could be used to correct systematic errors stemming from the statistical models.

The result of applying the re-scoring models to the tag profiles is computed using weighted intersecting composition by Silfverberg and Lindén (2009). After re-scoring, a best paths algorithm (Mohri and Riley, 2002) is used to extract the most probable analysis for the sentence.

## 5    Augmented HMM POS Tagger for English and Finnish

For English and Finnish we constructed POS taggers based on traditional second order HMMs augmented with models, which re-score lexical probabilitites according to tag context (this is the factor $p(w_i|t_{i-1}, t_i, t_{i+1})$ in the formula below). For the sentence $w_i$, ..., $w_n$, the taggers attempt to maximize the probability $p(t_1, ..., t_n|w_i, ..., w_n)$ over tag sequences $t_1$, ..., $t_n$. Because of the data sparseness problem, it is impossible to compute the probability directly, so the tagger instead maximizes its approximation

$$\prod_{i=1}^{n} p(t_i|t_{i-1}, t_{i-2})p(w_i|t_{i-1}, t_i, t_{i+1})p(w_i|t_i)$$

where the tag sequences $t_1 ..., t_n$ ranges over all analyses of the sentence. The term $p(t_i|t_{i-1}, t_{i-2})$ is the standard second order HMM approximation for the probability of the tag $t_i$. The term $p(w_i|t_{i-1}, t_i, t_{i+1})$ conditions the probability of the word $w_i$ on its tag context. Finally the term $p(w_i|t_i)$ is the standard HMM lexical probability.

In order to get the indices to match in the formula above, three additional symbols are needed, i.e. $t_{-1}$, $t_0$ and $t_{n+1}$ denote sentence boundary symbols, which are added during training and tagging for improved accuracy. Using sentence boundary symbols is adopted from Brants (2000).

In order to get some estimates for the probability of tag trigrams, which did not occur in the training data, we use tag bigram $p(t_i|t_{i-1})$ and tag unigram $p(t_i)$ models in parallel to the trigram model. Similarly we use models which assign probability $p(w_i|t_{i-1}, t_i)$ and $p(w_i|t_i, t_{i+1})$ in order to deal with previous unseen tag trigrams and wordforms. Of course the lexical model also weights analyses of words, serving as a backup model even in the case where the tag bigrams with the wordform were previously unseen.

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[1]Although the probabilities $p(t|w)$ would seem like a more natural choice in the lexical model, the approximation for probabilities used in the HMM model of the tagger require the inverted probabilities $p(w|t)$. For a more thorough discussion of HMMs see Manning and Schütze (1999).

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### 5.1 Lexical Models

For each tag $t$ and word $w$, our lexical model estimates the probability $p(w|t)$. For unknown words, we construct similar guessers as Brants (2000) and Halácsy et al. (2007). The guessers estimate the probability $p(w|t)$ using the probabilities $p(s_i|t)$ for each of the suffixes of $w$. These can be computed from training material. The estimate $p(w|t)$ is a smoothed sum of the estimates for all of the suffixes, as explained by Brants (2000).

Like Brants (2000), we train separate guessers for upper and lower case words. For Finnish, we additionally train a guesser for sentence initial words, because preliminary tests revealed that there were a lot of unknown sentence initial words. Using a separate guesser for these words yielded better results than using the upper case or the lower case guesser. For English, a separate guesser for sentence initial words does not improve accuracy.

For Finnish another modification was needed in addition to the added guesser. For unknown words, it seemed beneficial to use only the 10 highest ranking guesses. For English, reducing the number of guesses also reduces accuracy. The maximum number of guesses is therefore a parameter which needs to be estimated experimentally and can vary between languages.

### 5.2 Tag Sequence Models

We construct a set of finite-state transducers whose effect is equivalent to an HMM. For the sake of space reduction, we do not compile a single transducer equivalent to an HMM. Instead we split the HMM into component models, each of which weights n-grams of wordforms and tags in the sentence. We give a short overview here and refer to Silfverberg and Lindén (2010) for a more thorough discussion on how this is done.

We simulate the tag n-gram models of a second order HMM using six models compiled into transducers. We use one transducer which assigns probabilitites for the tag unigrams in the sentence, two transducers which assign probabilitites for tag bigrams and three transducers assigning probabilities for tag trigrams.

As an example of how the transducers operate, we explain the structure of the three transducers which assign probabilities to tag trigrams. As explained above: After lexical probabilities have been assigned to the words in a sentence, the

words and their analyses are compiled into a finite-state transducer, which assigns probabilities to the possible analyses of the entire sentence. Each of the three component models of the trigram model re-weight the paths of this transducer.

The first one of the models starts with the first three words (1st, 2nd and 3rd word) of the sentence and assigns a probability for each analysis trigram of the word triplet. It then moves on to the next three words (4th, 5th and 6th word) and their analyses, and so on. Hence the first model assigns a probability for each triplet of words and its analyses, which begins at indices $3k + 1$ in the sentence.

The second model skips the first word of the sentence, but after that it behaves as the first model re-scoring first the analyses of the triple (2nd, 3rd and 4th) and going on. As a result, it assigns probabilities to trigrams starting at indices $3k + 2$ in the sentence. By skipping the first two words, the third trigram model assigns weight to triplets beginning at indices $3k$. The net effect is that each trigram of wordforms and tags gets weighted once by the trigram model.

The models re-weighting tag bigrams and tag unigrams are constructed in an analogous way to the tag trigram models and the unigram bigram and trigram probabilities are smoothed using deleted interpolation, as suggested by Brants (2000).

Each of the models assigns a minimum penalty probability $1/(N + 1)$ to unknown tag n-grams. Here $N$ is the size of the training corpus.

### 5.3 Context Dependent Lexical Models

In addition to the transducers making up the HMM model, we construct context dependent lexical models, which assign probabilities

$$p(w_i|t_{i-1}, t_i, t_{i+1}), \ p(w_i|t_{i-1}, t_i), \ p(w_i|t_i, t_{i+1})$$

to word and tag combinations in analyses. The models which assign probabilities to word and tag bigram combinations are included in order to estimate the probability $p(w_i|t_{i-1}, t_i, t_{i+1})$ when the combination of $w_i$ with tags $t_{i-1}$, $t_i$ and $t_{i+1}$ has not been seen during training.

The context dependent lexical models are only applied to known words, but they do also provide additional improvement for tagging accuracy of unknown words by directly using neighboring words in estimating their tag profiles and proba-

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bilities. This is more reliable than using tag sequences.

The choice to only apply the models on known words is a convenient one. For known words context dependent lexical models were very easy for us to compile, since they are quite similar to ordinary tag n-gram models. Integrating them with the transducers making up the HMM model did not require any extra work besides estimating experimentally three coefficients which weight the models w.r.t. the HMM and each other. Weighted intersecting composition can be used to combine the sentence transducer and the re-scoring models regardless of how many models there are.

Similarly as in the HMM, unknown combinations of tags and words receive probability $1/(N+1)$, where $N$ is the training corpus size.

## 6 Data

We trained taggers for English and Finnish using corpora compiled from newspaper text.

For English we used the Wall Street Journal Corpus in the Penn Treebank. We adopted the practice, introduced by Collins (2000), to use sections 0-18 for training lexical and tag models, sections 19-21 for fine tuning (like computing deleted interpolation coefficients) and sections 22-24 for testing.

For Finnish, we used a morphologically analyzed and disambiguated corpus of news from the 1995 volume of Helsingin Sanomat, the leading Finnish newspaper[2] (We used the news from the KA section of the corpus).

The morphological tagging in the Finnish corpus is machine-made and it has not been checked manually. This soon becomes evident when one examines the corpus, since there are a number of tagging errors. Thus our results for Finnish have to be considered tentative.

Table 1 shows the number of tokens in the training, fine-tuning and test materials used to construct and evaluate the taggers. The tokenization of the corpora is used as is and all token counts include words and punctuation. As the table shows, token counts for the Finnish and English corpora are comparable.

|          | English         | Finnish          |
|----------|-----------------|------------------|
| Training | 969905          | 1027514          |
| Tuning   | 148158          | 181437           |
| Testing  | 171138 (2.43%)  | 156572 (10.41%)  |

Table 1: Summary of token counts for the data used for evaluation. The counts include words and punctuation. The amount of words, which were not seen during training, is indicated in parentheses.

|          | English | Finnish |
|----------|---------|---------|
| POS Tags | 81      | 776     |

Table 2: Number of POS tags in the Finnish and English corpora.

The amount of unknown words in the test corpus for Finnish is high. This is to be expected given the extensive morphology of the language. The extensive morphology is also reflected in the tag counts in table 2, which shows that the tag profile of the Finnish corpus is nearly ten times as large as the tag profile of the WSJ.[3]

Of the tags, in the Finnish corpus, 471 occur ten times or more, 243 occur one hundred times or more and 86 occur one thousand times or more. We conclude that there is a large number of tags which are fairly frequent. The corresponding figures for English are 58 tags occurring ten times or more, 44 tags occurring one hundred times or more and 38 tags occurring one thousand times or more.

The average number of possible analyses for words in the English corpus is 2.34. In the Finnish corpus, a word receives on average 1.45 analyses. The high number of analyses in the English corpus is partly explained by certain infrequent analyses of the frequent words "a" and "the". When these words are excluded, the average number of analyses drops to 2.06.

When reporting accuracy, we divide the number of correctly tagged tokens with the total number of tokens in the test material, i.e. accuracy counts include punctuation. In this we follow the ACLWiki State of the Art page for POS tagging[4]. All re-

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[2]Information about the corpus is available from http://www.csc.fi/english/research/software/ftc. It was compiled by The Research Institute for the Languages of Finland and CSC - IT Center for Science Ltd. The corpus can be obtained for academic use.

[3]There are 45 unique POS markers (such as NN and JJ) used in WSJ, but there are some unresolved ambiguities left in the corpus. That is why some words have POS tags consisting of more than one marker (eg. VBG|NN|JJ) making the total number of POS tags 81.

[4]http://www.aclweb.org/aclwiki/

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sults on accuracy are reported for the test materials, which were not seen during training.

## 7  Evaluation

We trained four separate taggers both for English and Finnish. The accuracies for the different models are shown in table 3.

|      | 1      | 2      | 3      | 4      |
|------|--------|--------|--------|--------|
| Eng  | 96.42% | 96.55% | 96.70% | 96.77% |
| Fin  | 95.56% | 95.87% | 95.98% | 96.02% |

1. Second order HMM.

2. Second order HMM augmented with lexical probabilities $p(w_i|t_{i-1}, t_i)$.

3. Second order HMM augmented with lexical probabilities $p(w_i|t_{i-1}, t_i)$ and $p(w_i|t_i, t_{i+1})$.

4. Second order HMM augmented with lexical probabilities $p(w_i|t_{i-1}, t_i)$, $p(w_i|t_i, t_{i+1})$ and $p(w_i|t_{i-1}, t_i, t_{i+1})$.

Table 3: Summary of tagging accuracies using different models. For Finnish, a separate guesser is used for sentence initial words.

The first tagger is a standard second order HMM. The only divergence from the HMM introduced by Brants (2000) is training a separate guesser for sentence initial words for Finnish and limiting the number of guesses to 10 for Finnish. This considerably improves the accuracy of the tagger from 94.91% to 95.56%.

The second tagger, we evaluate, is an HMM augmented by lexical probabilities conditioned on left tag context $p(w_i|t_{i-1}, t_i)$. This model roughly corresponds to the model Hunpos uses for POS tagging. As pointed out in section 5.3, the difference is that we do not estimate context dependent lexical probabilities for unknown words. This seems to lead to a slight reduction in accuracy.

In the third tagger, we add lexical probabilitites conditioned on right context $p(w_i|t_i, t_{i+1})$ and in the fourth tagger we add the final statistical model, which additionally uses lexical probabilities conditioned on both right and left tag context $p(w_i|t_{i-1}, t_i, t_{i+1})$.

The second tagger performs nearly as well as Hunpos and the third and fourth taggers perform better. This is to be expected, since the taggers in-

corporate right lexical context, which Hunpos cannot utilize.

|        | Seen   | Unseen | Overall |
|--------|--------|--------|---------|
| TnT    | 96.77% | 85.19% | 96.46%  |
| Hunpos | 96.88% | 86.13% | 96.58%  |
| Hfst   | 97.13% | 83.72% | 96.77%  |

Table 4: Summary of tagging accuracies for WSJ using TnT, Hunpos and Hfst. The accuracies are given for seen, unseen and all tokens. Hfst is our own tagger.

Table 4 shows accuracies for TnT, Hunpos and the best of our models, which we call **Hfst**, when tagging WSJ. It clearly performs the best out of all the taggers on all tokens and it has very high accuracy on known tokens. For unknown words, its accuracy is nevertheless somewhat lower than for TnT and Hunpos.

|        | Seen   | Unseen | Overall |
|--------|--------|--------|---------|
| Hunpos | 98.06% | 76.83% | 95.62%  |
| Hfst   | 97.98% | 81.04% | 96.02%  |

Table 5: Summary of tagging accuracies for the Finnish test corpus using Hunpos and Hfst. The accuracies are given for seen, unseen and all tokens. Hfst is our own tagger.

Table 5 shows accuracies for Hunpos and Hfst on the Finnish test corpus. The accuracy on known words is markedly high for both taggers. This is probably partly due to the low average number of analyses per word, which makes analyzing known words easier than in English text. Conversely, the accuracy on unknown words is quite low and much lower for Hunpos than for Hfst.

By increasing the number of guesses from 10 to 40 for unknown words, we accomplish a similar reduction in accuracy on unknown words (from 81.04% to 79.29%) for Hfst as Hunpos exhibits. This points to the direction that the problems Hunpos encounters in tagging unknown Finnish words are in fact due to its unrestricted guesser.

In conclusion, the Hfst tagger has better overall performance than both Hunpos and TnT.

## 8  Discussion and Future Work

Because of extensive and fairly regular morphology, words in Finnish contain a lot of information about their part-of-speech and inflection. Hence

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words which share long suffixes are probably more likely to get the same correct POS analysis in Finnish than in English.

By considering more guesses for a Finnish unknown word, one at the same time considers more guesses which were suggested on basis of words with short suffixes in common with the unknown word. This problem is worsened by smoothing, which reduces the differences between the probabilities of suggestions. In fact we believe that this implies that the kind of guesser suggested by Brants (2000) and used in Hunpos is not the ideal choice for Finnish. And an architecture which makes it possible to try out different guesser designs, could make a tagger toolkit adaptable for a larger variety of languages than a traditional HMM.

The need for an added guesser for sentence initial words in Finnish can be understood rather easily by examining the test corpus. Sentences are fairly short, on average 10.3 words. The number of unknown words in the corpus is high and sentence initial words are not an exception. Both using the guesser for lower case words and upper case words produces poor results, because the first one underestimates the number of proper names among sentence initial words and the second one grossly overestimates it. Hence a guesser trained either on all words in the test material or only sentence initial words is needed.

The need for a sentence initial guesser in fact speaks in favor of Hunpos, since it incorporates a contextually dependent lexical model also for unknown words. Therefore it needs no special tweaks in order to perform well on sentence boundaries. Still, our baseline second order HMM achieves 95.56% which is extremely close to Hunpos 95.62%. The baseline model uses context dependent lexical probabilities only in the sense that it uses the separate guesser for sentence initial words. Perhaps this is indeed the only place where a context sensitive guesser has added effect in the Finnish corpus.

There is a lot of work left with the Hfst tagger. The accuracy of the guesser needs to be improved even when tagging English. There should not be any reason why it could not be made at least as accurate as the guesser in TnT.

Another improvement would be a rule compiler which compiles hand-written rules into sequential models, that are compatible with the statistical models which are used currently. Especially for Finnish, such a rule compiler would be a significant asset, because e.g. the disambiguation of analyses of verb forms often leads to long distance dependencies, which n-gram models capture poorly. It is not evident how TnT or Hupos could be adapted to using e.g. hand-written tagging rules in order to improve performance. But it would be an easy task for Hfst, if only there existed a suitable rule compiler.

A third direction of future work, would be to try the framework for other sequential labelling tasks such as tokenizing, chunking and named entity recognition.

## 9   Conclusion

We have demonstrated a framework for constructing POS taggers, which is capable of incorporating a variety of knowledge sources for POS tagging. We showed that it is possible, even straight forward, to combine different statistical models into one tagger. We hope that we have also demonstrated that it would be fairly straight forward to incorporate other kinds of models as well.

We constructed taggers for English and Finnish, which obtain superior accuracy compared to two widely known and used taggers TnT and Hunpos based on HMMs. For Finnish we modified the guessers used to tag unknown words in order to achieve added accuracy. Because of the modular design of our system, this did not require changes in any of the other models. We believe that the accuracy on tagging Finnish 96.02% shows that our taggers can be successfully adapted to languages which differ substantially from English.

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# Improving Finite-State Spell-Checker Suggestions with Part of Speech N-Grams

Tommi A Pirinen and Miikka Silfverberg and Krister Lindén

University of Helsinki
Department of Modern Languages
University of Helsinki, 00014
tommi.pirinen@helsinki.fi, miikka.silfverberg@helsinki.fi, krister.linden@helsinki.fi

**Abstract.** In this paper we demonstrate a finite-state implementation of context-aware spell checking utilizing an N-gram based part of speech (POS) tagger to rerank the suggestions from a simple edit-distance based spell-checker. We demonstrate the benefits of context-aware spell-checking for English and Finnish and introduce modifications that are necessary to make traditional N-gram models work for morphologically more complex languages, such as Finnish.

## 1   Introduction

Spell-checking by computer is perhaps one of the oldest and most researched applications in the field of language technology starting from the mid 20th century [3]. One of the crucial parts of spell-checking—both from an interactive user-interface point of view and for unsupervised correction of errors—is the production of spelling suggestions. In this article we test various finite-state methods for using context and shallow morphological analysis to improve the suggestions generated by traditional edit distance measures or unigram frequencies such as [12].

The spell-checking task can be split into two parts, i.e. *detection* and actual *correction* of the spelling errors. The spelling errors can be detected in text as word forms that are unlikely to belong to the natural language in question, such as writing 'cta' instead of 'cat'. This form of spelling errors is commonly called *non-word (spelling) errors*. Another form of spelling errors is word forms that do not belong to the given context under certain syntactic or semantic requirements, such as writing 'their' instead of 'there'. This form is correspondingly called *real-word (spelling) errors*. The non-word type of spelling errors can easily be detected using a dictionary, whereas the detection of the latter type of errors typically requires syntactic analysis or probabilistic methods [8]. For the purpose of this article we do not distinguish between them, as the same correction methods can be applied to both.

The correction of spelling errors usually means generating a list of word forms belonging to the language for a user to chose from. The mechanism for generating correction suggestions for the erroneous word-forms is an *error-model*. The

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purpose of an error-model is to act as a filter to revert the mistakes the user typing the erroneous word-form has made. The simplest and most traditional model for making such corrections is the Levenshtein-Damerau edit distance algorithm, attributed initially to [6] and especially in the context of spell-checking to [3]. The Levenshtein-Damerau edit distance assumes that spelling errors are one of insertion, deletion or changing of a single character to another, or swapping two adjacent characters, which models well the spelling errors caused by an accidental slip of finger on a keyboard. It was originally discovered that for most languages and spelling errors, this simple method already covers 80 % of all spelling errors [3]. This model is also language-independent, ignoring the differences in character repertoires of a given language. Various other error models have also been developed, ranging from confusion sets to phonemic folding [5].

In this paper, we evaluate the use of context for further fine-tuning of the correction suggestions. The context is still not commonly used in spell-checkers. According to [5] it was lacking in the majority of spell-checkers and while the situation may have improved slightly for some commercial office suite products, the main spell-checkers for open source environments are still primarily context-ignorant, such as hunspell[1] which is widely used in the open source world. For English, the surface word-form trigrams model has been demonstrated to be reasonably efficient both for non-word cases [2] and for for real-word cases[7]. As an additional way to improve the set of suggestions, we propose to use morphosyntactically relevant analyses in context. In this article, we evaluate a model with a statistical morphological tagger [14].

The system described is fully built on freely available tools and data, available for download and use from `http://hfst.svn.sourceforge.net/viewvc/hfst/trunk/cicling-2011-contextspell/`. The only exception to this is the training data for Finnish, since there is no available morphological training data for Finnish as of yet, the download does not contain the source material for training but only the trigram models compiled into binary format automata.

Furthermore, we test the context-based spelling methods using both English and Finnish language materials to ensure the applicability of the method for morphologically different languages. The reason for doing this is two-fold; firstly the fact that English has rather low morphological productivity may make it behave statistically differently from other languages. On the other hand, English has the largest amount of freely available text corpora. For other languages, the availability of free corpora, especially annotated material, is often seen as a problem.

The article is laid out as follows: In Section 2, we outline the implementation of a finite-state context-aware spell-checker and describe the statistical methods used. In Section 3, we introduce the corpora and dictionaries used for spell-checking and training material as well as the corpora used for obtaining the spelling errors with context. In Section 4, we show how the created spelling correctors improve the results and explain the errors left. In Section 5, we com-

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[1] `http://hunspell.sf.net`

pare our work to other current systems and enumerate possible improvements
for both.

## 2   Methods

The spelling correction in this article is performed in several phases: assum-
ing misspelled word *cta* for *cat*, we first apply the error model to the already
known incorrect string *cta* to produce candidates for probable mistypings. For
this purpose we use the Damerau-Levenshtein edit-distance algorithm in finite-
state form. When applied to *cta* we get all strings with one or two typing mis-
takes, i.e. *ata*, *bta*, ..., *acta*, *bcta*, ..., *ta*, *ca*, ..., *tca*, and the correct *cat*. This
set of strings is simultaneously matched against the language model, which will
produce a set of corrections, such as *cat*, *act* or *car*. Since both the error-model
and the language model contain information on likelihoods of errors and words
respectively, the resulting list will be sorted according to a combination of the
edit distance measure and the probability of the word in a reference corpus. The
rankings based on edit distance alone and the edit distance combined with word
probabilities form our two baseline models.

The context-based models we introduce here use the suggestion list gained
from a contextless spelling-checker and the context of the words as input to
rerank suggestions based on N-gram models. Each of the suggestions is tried
against the N-gram models, and the ones with higher likelihoods will be lifted.
For example when correcting the misspelling of 'an' as 'anx' in the sentence "this
is anx example sentence", as shown in the Table 1, we have the surface trigrams
{this, is, _}, {is, _, example}, {_, example, sentence}, and corresponding analy-
sis trigrams {DET, VVBZ, _}, {VVBZ, _, NN}, {_, NN, NN}. The suggestions
for anx at edit distance one include 'ax', 'an' (one deletion), 'ant', 'and', 'any'
(one change) and so on. To rank the possible suggestions, we substitute $s_3$ with
the suggestions, and calculate the likelihood of their analyses.

**Table 1.** Example trigram combinations

| $\text{this}_{s_1}$ | $\text{is}_{s_2}$ | $\_s_3$ | $\text{example}_{s_4}$ | $\text{sentence}_{s_5}$ |
|---|---|---|---|---|
| $\text{DET}_{a_1}$ | $\text{VVBZ}_{a_2}$ | $\_\ a_3$ | $\text{NN}_{a_4}$ | $\text{NN}_{a_5}$ |

### 2.1   Weighted Finite-State Interpretation of the Method

In this article we use a finite-state formulation of spell-checking. We assume
the standard notation for finite-state algebra and define the language model as
a weighted finite-state automaton assigning a weight to each correctly spelled
word-form of a language, and an error model automaton mapping a misspelled

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string to a set of corrected strings and their weights. The probabilistic interpretation of the components is such that the weighted fsa as a language model assigns weight $w(s)$ to word $s$ corresponding to the probability $P(s)$ for the word to be a correct word in the language. The error model assigns weight $w(s : r)$ to string pair $s, r$ corresponding to the probability $P(s|r)$ of a user writing word r when intending to write the word $s$, and the context model assigns weight $w(s_3a_3)$ to word $s_3$ with associated POS tagging $a_3$ corresponding to the standard HMM estimate $P(a_3s_3)$ of the analysis being in a 3-gram context given by equation (1).

$$P(a_3s_3) = \prod_{i=3}^{5} P(s_i|a_i)P(a_i|a_{i-2}, \ a_{i-1}) \tag{1}$$

In a weighted finite-state system, the probabilistic data needs to be converted to the algebra supported by the finite-state weight structure. In this case we use the tropical semi-ring by transforming the frequencies into penalty weights with the formula $-\log \frac{f}{CS}$, where $f$ is the frequency and $CS$ the corpus size in number of tokens. If the language model allows for words that are not in the dictionary, a maximal weight is assigned to the unseen word forms that may be in the language model but not in the training corpus, i.e. any unseen word has a penalty weight of $-\log \frac{1}{CS}$.

The spelling corrections suggested by these unigram lexicon-based spell-checkers are initially generated by composing an edit-distance automaton [13] with an error weight corresponding to the probability of the error estimated in a corpus, i.e. $-\log \frac{f_F}{CS+1}$, where $f_F$ is the frequency of the misspelling in a corpus. This weight is attached to the edit distance type error. In practice, this typically still means that the corrections are initially ordered primarily by the edit distance of the correction, and secondarily by the unigram frequency of the word-form in the reference corpus. This order is implicitly encoded in the weighted paths of the resulting automaton; to list the corrections we use the n-best paths algorithm [9]. This ordering is also used as our second baseline.

For a context-based reordering of the corrections, we use the POS tagging probabilities for the given suggestions. The implementation of the analysis N-gram probability estimation is similar to the one described in [14] with the following adaptations for the spelling correction. For the suggestion which gives the highest ranking, the most likely analysis is selected. The N-gram probability is estimated separately for each spelling suggestion and then combined with the baseline probability given by the unigram probability and the edit distance weight. The ideal scaling for the weights of unigram probabilities, i.e. edit distance probabilities with respect to N-gram probabilities, was acquired by performing tests on an automatically generated spelling error corpus.

The resulting finite-state system consists of three sets of automata, i.e. the dictionary for spell-checking, the error-model as described in [12], and the new N-gram model automata. The automata sizes are given in Table 2 for reference. The sizes also give an estimate of the memory usage of the spell-checking system, although the actual memory-usage during correction will rise depending on the actual extent of the search space during the correction phase.

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**Table 2.** Automata sizes.

| Automaton | States | Transitions | Bytes |
|---|---|---|---|
| **English** | | | |
| Dictionary | 25,330 | 42,448 | 1.2 MiB |
| Error model | 1,303 | 492,232 | 5.9 MiB |
| N-gram lexicon | 363,053 | 1,253,315 | 42 MiB |
| N-gram sequences | 46,517 | 200,168 | 4.2 MiB |
| **Finnish** | | | |
| Dictionary | 179,035 | 395,032 | 16 MiB |
| Error model | 1,863 | 983,227 | 12 MiB |
| N-gram lexicon | 70,665 | 263,298 | 8.0 MiB |
| N-gram sequences | 3,325 | 22,418 | 430 KiB |

## 2.2 English-Specific Finite-State Weighting Methods

The language model for English was created as described in [10]. [2]. It consists of the word-forms and their probabilities in the corpora. The edit distance is composed of the standard English alphabet with an estimated error likelihood of 1 in 1000 words. Similarly for the English N-gram material, the initial analyses found in the WSJ corpus were used in the finite-state tagger as such. The scaling factor between the dictionary probability model and the edit distance model was acquired by estimating the optimal multipliers using the automatic misspellings and corrections of a Project Gutenberg Ebook[3] *Alice's Adventures in Wonderland.*

## 2.3 Finnish-Specific Finite-State Weighting Methods

The Finnish language model was based on a readily-available morphological weighted analyser of Finnish language [11]. We further modified the automaton to penalize suggestions with newly created compounds and derivations by adding a weight greater than the maximum to such suggestions, i.e. $-A \log \frac{1}{CS+1}$ in the training material. This has nearly the same effect as using a separate dictionary for suggestions that excludes the heavily weighted forms without requiring the extra space. Also for Finnish, a scaling factor was estimated by using automatic misspellings and corrections of a Project Gutenberg Ebook[4] *Juha.*

In the initial Finnish tagger, there was a relatively large tagset, all of which did not contain information necessary for the task of spell-checking, such as discourse particles, which are relatively context-agnostic [4], so we opted to simplify the tagging in these cases. Furthermore, the tagger used for training produced

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[2] The finite-state formulation of this is informally described in `http://blogs.helsinki.fi/tapirine/2011/07/21/how-to-write-an-hfst-spelling-corrector/`

[3] `http://www.gutenberg.org/cache/epub/11/pg11.txt`

[4] `http://www.gutenberg.org/cache/epub/10863/pg10863.txt`

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heuristic readings for unrecognized word-forms, which we also removed. Finally, we needed to add some extra penalties to the word forms unknown to the dictionary in the N-gram model, since this phenomenon was more frequent and diverse for Finnish than English.

## 3 Material

To train the spell-checker lexicons, word-form probabilities can be acquired from arbitrary running text. By using unigram frequencies, we can assign all word-forms some initial probabilities in isolation, i.e. with no spell-checking context. The unigram-trained models we used were acquired from existing spell-checker systems [10, 12], but we briefly describe the used corpora here as well.

To train the various N-gram models, corpora are required. For the surface-form training material, it is sufficient to capture running N-grams in the text. For training the statistical tagger with annotations, we also require disambiguated readings. Ideally of course this means hand-annotated tree banks or similar gold standard corpora.

The corpora used are summarized in Table 3. The sizes are provided to make it possible to reconstruct the systems. In practice, they are the newest available versions of the respective corpora at the time of testing. In the table, the first row is the training material used for the finite-state lexicon, i.e. the extracted surface word-forms without the analyses for unigram training. The second row is for the analyzed and disambiguated material for the N-gram based taggers for suggestion improvement. The third line is the corpora of spelling errors used only for the evaluation of the systems. As we can see from the figures of English compared with Finnish, there is a significant difference in freely available corpora such as Wikipedia. When going further to lesser resourced languages, the number will drop enough to make such statistical approaches less useful, e.g. Northern Sámi in [12].

**Table 3.** Sizes of training and evaluation corpora.

|          | Sentences | Tokens        | Word-forms |
|----------|-----------|---------------|------------|
| **English** | | | |
| Unigrams |           | 2,110,728,338 | 128,457    |
| N-grams  | 42,164    | 969,905       | 39,690     |
| Errors   | 85        | 606           | 217        |
| **Finnish** | | | |
| Unigrams |           | 17,479,297    | 968,996    |
| N-grams  | 98,699    | 1,027,514     | 144,658    |
| Errors   | 333       | 4,177         | 2,762      |

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### 3.1   English corpora

The English dictionary is based on a frequency weighted word-form list of the English language as proposed in [10]. The word-forms were collected from the English Wiktionary[5], the English EBooks from the project Gutenberg[6] and the British National Corpus[7]. This frequency weighted word-list is in effect used as a unigram lexicon for spell-checking.

To train an English morphosyntactic tagger, we use the WSJ corpus. In this corpus each word is annotated by a single tag that encodes some morphosyntactic information, such as part-of-speech and inflectional form. The total number of tags in this corpus is 77 [8].

The spelling errors of English were acquired by extracting the ones with context from the Birkbeck error corpus[9]. In this corpus, the errors are from a variety of sources, including errors made by children and language-learners. For the purpose of this experiment we picked the subset of errors which had context and also removed the cases of word joining and splitting to simplify the implementation of parsing and suggestion.

### 3.2   Finnish Corpora

As the Finnish dictionary, we selected the freely available open source finite-state implementation of a Finnish morphological analyser[10]. The analyser had the frequency-weighted word-form list based on Finnish Wikipedia[11] making it in practice an extended unigram lexicon for Finnish. The Finnish morphological analyser, however, is capable of infinite compounding and derivation, which makes it a notably different approach to spell checking than the English finite word-form list.

The Finnish morphosyntactic N-gram model was trained using a morphosyntactically analyzed Finnish Newspaper[12]. In this format, the annotation is based on a sequence of tags, encoding part of speech and inflectional form. The total number of different tag sequences for this annotation is 747.

For Finnish spelling errors, we ran the Finnish unigram spell-checker through Wikipedia, europarl and a corpus of Finnish EBooks from the project Gutenberg[13] to acquire the non-word spelling errors, and picked at random the errors

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[5] http://en.wiktionary.org

[6] http://www.gutenberg.org/browse/languages/en

[7] http://www.kilgarriff.co.uk/bnc-readme.html

[8] We used a deprecated version of the Penn Treebank where the tag set includes compound tags like VB|NN in addition to the usual Penn Treebank tags. For the final version of the article we will rerun the tests on the regular WSJ corpus.

[9] http://ota.oucs.ox.ac.uk/headers/0643.xml

[10] http://home.gna.org/omorfi

[11] http://download.wikipedia.org/fiwiki/

[12] http://www.csc.fi/english/research/software/ftc

[13] http://www.gutenberg.org/browse/languages/fi

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having frequencies in range 1 to 8 instances; a majority of higher frequency non-words were actually proper nouns or neologisms missing from the dictionary. Using all of Wikipedia, europarl and Gutenberg provides a reasonable variety of both contemporary and old texts in a wide range of styles.

## 4  Tests and Evaluation

The evaluation of the correction suggestion quality is described in Table 4. The Table 4 contains the precision for the spelling errors. The precision is measured by ranked suggestions. In the tables, we give the results separately for ranks 1—5, and then for the accumulated ranks 1—10. The rows of the table represent different combinations of the N-gram models. The first row is a baseline score achieved by the weighted edit distance model alone, and the second is with unigram-weighted dictionary over edit-distance 2. The last two columns are the traditional word-form N-gram model and our POS tagger based extension to it.

**Table 4.** Precision of suggestion algorithms with real spelling errors.

| Algorithm | 1 | 2 | 3 | 4 | 5 | 1—10 |
|---|---|---|---|---|---|---|
| **English** | | | | | | |
| Edit distance 2 (baseline) | 25.9 % | 2.4 % | 2.4 % | 1.2 % | 3.5 % | 94.1 % |
| Edit distance 2 with Unigrams | 28.2 % | 5.9 % | 29.4 % | 3.5% | 28.2 % | 97.6 % |
| Edit distance 2 with Word N-grams | 29.4 % | 10.6 % | 34.1 % | 5.9 % | 14.1 % | 97.7 % |
| Edit distance 2 with POS N-grams | 68.2 % | 18.8 % | 3.5 % | 2.4 % | 0.0 % | 92.9 % |
| **Finnish** | | | | | | |
| Edit distance 2 (baseline) | 66.5 % | 8.7 % | 4.0 % | 4.7 % | 1.9 % | 89.8 % |
| Edit distance 2 with Unigrams | 61.2 % | 13.4 % | 1.6 % | 3.1 % | 3.4 % | 88.2 % |
| Edit distance 2 with Word N-grams | 65.0 % | 14.4 % | 3.8 % | 3.1 % | 2.2 % | 90.6 % |
| Edit distance 2 with POS N-grams | 71.4 % | 9.3 % | 1.2 % | 3.4 % | 0.3 % | 85.7 % |

It would appear that POS N-grams will in both cases give a significant boost to the results, whereas the word-form N-grams will merely give a slight increase to the results. In next subsections we further disect the specific changes to results the different approaches give.

### 4.1  English Error-Analysis

In [10], the authors identify errors that are not solved using simple unigram weights, such as correcting *rember* to *remember* instead of *member*. Here, our scaled POS N-gram context-model as well as the simpler word N-gram model, which can bypass the edit distance model weight will select the correct suggestion. However, when correcting e.g. *ment* to *meant* in stead of *went* or *met* the POS based context reranking gives no help as the POS stays the same.

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## 4.2   Finnish Error-Analysis

In Finnish results we can easily notice that variation within the first position in the baseline results and reference system is more sporadic. This can be traced back to the fuzz factor caused by a majority of probabilities falling into the same category in our tests. The same edit-distance and unigram probability leaves the decision to random factors irrelevant to this experiment, such as alphabetical ordering that comes from data structures backing up the program code. The N-gram based reorderings are the only methods that can tiebreak the results here.

An obvious improvement for Finnish with POS N-grams comes from correcting agreeing NP's towards case agreement, such as *yhdistetstä* to *yhdisteistä* ('of compounds' Pl Ela) instead of the statistically more common *yhdisteestä* ('of compound' Sg Ela). However, as with English, the POS information does fail to rerank cases where two equally rare word-forms with the same POS occur at the same edit distance, which seems to be common with participles, such as correcting *varustunut* to *varautunut* in stead of *varastanut*.

Furthermore we note that the the discourse particles that were dropped from the POS tagger's analysis tag set in order to decrease the tag set size will cause certain word forms in the dictionary to be incorrectly reranked, such as when correcting the very common misspelling *muillekkin* into *muillekokin* ('for others as well?' Pl All Qst Kin) instead of the originally correct *muillekin* ('for others as well' Pl All Kin), since the analyses Qst (for question enclitic) and Kin (for additive enclitic) are both dropped from the POS analyses.

## 4.3   Performance Evaluation

We did not work on optimizing the N-gram analysis and selection, but we found that the speed of the system is reasonable—even in its current form. Table 5 summarizes the average speed of performing the experiments in Table 4.

**Table 5.** The speed of ranking the errors.

| Material Algorithm | English | Finnish |
|---|---|---|
| Unigram (baseline) | 10.0 s | 51.8 s |
|  | 399.1 wps | 6.2 wps |
| POS N-grams | 377.4 s | 1616.2 s |
|  | 10.6 wps | 0.14 wps |

The performance penalty that is incurred on Finnish spell-checking but not so much on English comes from the method of determining readings for words unknown to the language model, i.e. from the guessing algorithm. The amount of words unknown to the language model in Finnish was greater than for English

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due to the training data sparseness and the morphological complexity of the language.

## 5   Future Work and Discussion

We have shown that the POS based N-gram models are suitable for improving the spelling corrections for both morphologically more complex languages such as Finnish and for further improving languages with simpler morphologies like English. To further verify the claim, the method may still need to be tested on a typologically wider spectrum of languages.

In this article, we used readily available and hand-made error corpora to test our error correction method. A similar method as the one we use for error correction should be possible in error detection as well, especially when detecting real-word errors [7]. In future research, an obvious development is to integrate the N-gram system as a part of a real spell-checker system for both detection and correction of spelling errors, as is already done for the unigram based spell checker demonstrated in [12].

The article discussed only the reranking over basic edit distance error models, further research should include more careful statistical training for the error model as well, such as one demonstrated in [1].

## 6   Conclusion

In this paper we have demonstrated the use of finite-state methods for trigram based generation of spelling suggestions. We have shown that the basic word-form trigram methods suggested for languages like English do not seem to be as useful without modification for morphologically more complex languages like Finnish. Instead a more elaborate N-gram scheme using POS n-grams is successful for Finnish as well as English.

### Acknowledgements

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# Accelerated Estimation of Conditional Random Fields using a Pseudo-Likelihood-inspired Perceptron Variant

**Teemu Ruokolainen**[a]     **Miikka Silfverberg**[b]     **Mikko Kurimo**[a]     **Krister Lindén**[b]

[a] Department of Signal Processing and Acoustics, Aalto University, firstname.lastname@aalto.fi
[b] Department of Modern Languages, University of Helsinki, firstname.lastname@helsinki.fi

## Abstract

We discuss a simple estimation approach for conditional random fields (CRFs). The approach is derived heuristically by defining a variant of the classic perceptron algorithm in spirit of pseudo-likelihood for maximum likelihood estimation. The resulting approximative algorithm has a linear time complexity in the size of the label set and contains a minimal amount of tunable hyper-parameters. Consequently, the algorithm is suitable for learning CRF-based part-of-speech (POS) taggers in presence of large POS label sets. We present experiments on five languages. Despite its heuristic nature, the algorithm provides surprisingly competetive accuracies and running times against reference methods.

## 1 Introduction

The conditional random field (CRF) model (Lafferty et al., 2001) has been successfully applied to several sequence labeling tasks in natural language processing, including part-of-speech (POS) tagging. In this work, we discuss accelerating the CRF model estimation in presence of a large number of labels, say, hundreds or thousands. Large label sets occur in POS tagging of morphologically rich languages (Erjavec, 2010; Haverinen et al., 2013).

CRF training is most commonly associated with the (conditional) maximum likelihood (ML) criterion employed in the original work of Lafferty et al. (2001). In this work, we focus on an alternative training approach using the averaged perceptron algorithm of Collins (2002). While yielding competitive accuracy (Collins, 2002; Zhang and Clark, 2011), the perceptron algorithm avoids extensive tuning of hyper-parameters and regularization re-quired by the stochastic gradient descent algorithm employed in ML estimation (Vishwanathan et al., 2006). Additionally, while ML and perceptron training share an identical time complexity, the perceptron is in practice faster due to sparser parameter updates.

Despite its simplicity, running the perceptron algorithm can be tedious in case the data contains a large number of labels. Previously, this problem has been addressed using, for example, $k$-best beam search (Collins and Roark, 2004; Zhang and Clark, 2011; Huang et al., 2012) and parallelization (McDonald et al., 2010). In this work, we explore an alternative strategy, in which we modify the perceptron algorithm in spirit of the classic *pseudo-likelihood* approximation for ML estimation (Besag, 1975). The resulting novel algorithm has linear complexity w.r.t. the label set size and contains only a single hyper-parameter, namely, the number of passes taken over the training data set.

We evaluate the algorithm, referred to as the *pseudo-perceptron*, empirically in POS tagging on five languages. The results suggest that the approach can yield competitive accuracy compared to perceptron training accelerated using a violation-fixed 1-best beam search (Collins and Roark, 2004; Huang et al., 2012) which also provides a linear time complexity in label set size.

The rest of the paper is as follows. In Section 2, we describe the pseudo-perceptron algorithm and discuss related work. In Sections 3 and 4, we describe our experiment setup and the results, respectively. Conclusions on the work are presented in Section 5.

## 2 Methods

### 2.1 Pseudo-Perceptron Algorithm

The (unnormalized) CRF model for input and output sequences $x = (x_1, x_2, \ldots, x_{|x|})$ and

$y = (y_1, y_2, \ldots, y_{|x|})$, respectively, is written as

$$p\left(y \mid x; \boldsymbol{w}\right) \propto \exp\left(\boldsymbol{w} \cdot \boldsymbol{\Phi}(y, x)\right)$$

$$= \prod_{i=n}^{|x|} \exp\left(\boldsymbol{w} \cdot \boldsymbol{\phi}(y_{i-n}, \ldots, y_i, x, i)\right),$$

(1)

where $\boldsymbol{w}$ denotes the model parameter vector, $\boldsymbol{\Phi}$ the vector-valued global feature extracting function, $\boldsymbol{\phi}$ the vector-valued local feature extracting function, and $n$ the model order. We denote the tag set as $\mathcal{Y}$. The model parameters $\boldsymbol{w}$ are estimated based on training data, and test instances are decoded using the Viterbi search (Lafferty et al., 2001).

Given the model definition (1), the parameters $\boldsymbol{w}$ can be estimated in a straightforward manner using the structured perceptron algorithm (Collins, 2002). The algorithm iterates over the training set a single instance $(x, y)$ at a time and updates the parameters according to the rule $\boldsymbol{w}^{(i)} = \boldsymbol{w}^{(i-1)} + \Delta\boldsymbol{\Phi}(x, y, z)$, where $\Delta\boldsymbol{\Phi}(x, y, z)$ for the $i$th iteration is written as $\Delta\boldsymbol{\Phi}(x, y, z) = \boldsymbol{\Phi}(x, y) - \boldsymbol{\Phi}(x, z)$. The prediction $z$ is obtained as

$$z = \arg\max_{u \in \mathcal{Y}(x)} \boldsymbol{w} \cdot \boldsymbol{\Phi}(x, u) \qquad (2)$$

by performing the Viterbi search over $\mathcal{Y}(x) = \mathcal{Y} \times \cdots \times \mathcal{Y}$, a product of $|x|$ copies of $\mathcal{Y}$. In case the perceptron algorithm yields a small number of incorrect predictions on the training data set, the parameters generalize well to test instances with a high probability (Collins, 2002).

The time complexity of the Viterbi search is $O(|x| \times |\mathcal{Y}|^{n+1})$. Consequently, running the perceptron algorithm can become tedious if the label set cardinality $|\mathcal{Y}|$ and/or the model order $n$ is large. In order to speed up learning, we define a variant of the algorithm in the spirit of pseudo-likelihood (PL) learning (Besag, 1975). In analogy to PL, the key idea of the pseudo-perceptron (PP) algorithm is to obtain the required predictions over single variables $y_i$ while fixing the remaining variables to their true values. In other words, instead of using the Viterbi search to find the $z$ as in (2), we find a $z'$ for each position $i \in 1..|x|$ as

$$z' = \arg\max_{u \in \mathcal{Y}'_i(x)} \boldsymbol{w} \cdot \boldsymbol{\Phi}(x, u), \qquad (3)$$

with $\mathcal{Y}'_i(x) = \{y_1\} \times \cdots \times \{y_{i-1}\} \times \mathcal{Y} \times \{y_{i+1}\} \times \cdots \times \{y_{|x|}\}$. Subsequent to training, test instances

are decoded in a standard manner using the Viterbi search.

The appeal of PP is that the time complexity of search is reduced to $O(|x| \times |\mathcal{Y}|)$, i.e., linear in the number of labels in the label set. On the other hand, we no longer expect the obtained parameters to necessarily generalize well to test instances.[1] Consequently, we consider PP a heuristic estimation approach motivated by the rather well-established success of PL (Korč and Förstner, 2008; Sutton and McCallum, 2009).[2]

Next, we study yet another heuristic pseudo-variant of the perceptron algorithm referred to as the *piecewise-pseudo-perceptron* (PW-PP). This algorithm is analogous to the piecewise-pseudo-likelihood (PW-PL) approximation presented by Sutton and McCallum (2009). In this variant, the original graph is first split into smaller, possibly overlapping subgraphs (pieces). Subsequently, we apply the PP approximation to the pieces. We employ the approach coined *factor-as-piece* by Sutton and McCallum (2009), in which each piece contains $n + 1$ consecutive variables, where $n$ is the CRF model order.

The PW-PP approach is motivated by the results of Sutton and McCallum (2009) who found PW-PL to increase stability w.r.t. accuracy compared to plain PL across tasks. Note that the piecewise approximation in itself is not interesting in chain-structured CRFs, as it results in same time complexity as standard estimation. Meanwhile, the PW-PP algorithm has same time complexity as PP.

## 2.2 Related work

Previously, impractical running times of perceptron learning have been addressed most notably using the $k$-best beam search method (Collins and Roark, 2004; Zhang and Clark, 2011; Huang et al., 2012). Here, we consider the "greedy" 1-best beam search variant most relevant as it shares the time complexity of the pseudo search. Therefore, in the experimental section of this work, we compare the PP and 1-best beam search.

We are aware of at least two other learning approaches inspired by PL, namely, the pseudo-max and piecewise algorithms of Sontag et al. (2010) and Alahari et al. (2010), respectively. Compared to these approaches, the PP algorithm provides a simpler estimation tool as it avoids the

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[1]We leave formal treatment to future work.
[2]Meanwhile, note that pseudo-likelihood is a consistent estimator (Gidas, 1988; Hyvärinen, 2006).

hyper-parameters involved in the stochastic gradient descent algorithms as well as the regularization and margin functions inherent to the approaches of Alahari et al. (2010) and Sontag et al. (2010). On the other hand, Sontag et al. (2010) show that the pseudo-max approach achieves consistency given certain assumptions on the data generating function. Meanwhile, as discussed in previous section, we consider PP a heuristic and do not provide any generalization guarantees. To our understanding, Alahari et al. (2010) do not provide generalization guarantees for their algorithm.

## 3  Experimental Setup

### 3.1  Data

For a quick overview of the data sets, see Table 1.

**Penn Treebank.**    The first data set we consider is the classic Penn Treebank. The complete treebank is divided into 25 sections of newswire text extracted from the Wall Street Journal. We split the data into training, development, and test sets using the sections 0-18, 19-21, and 22-24, according to the standardly applied division introduced by Collins (2002).

**Multext-East.**    The second data we consider is the multilingual Multext-East (Erjavec, 2010) corpus.   The corpus contains the novel *1984* by George Orwell.   From the available seven languages, we utilize the Czech, Estonian and Romanian sections.  Since the data does not have a standard division to training and test sets, we assign the 9th and 10th from each 10 consecutive sentences to the development and test sets, respectively. The remaining sentences are assigned to the training sets.

**Turku Dependency Treebank.**    The third data we consider is the Finnish Turku Dependency Treebank (Haverinen et al., 2013). The treebank contains text from 10 different domains. We use the same data split strategy as for Multext East.

### 3.2  Reference Methods

We compare the PP and PW-PP algorithms with perceptron learning accelerated using 1-best beam search modified using the early update rule (Huang et al., 2012). While Huang et al. (2012) experimented with several violation-fixing methods (early, latest, maximum, hybrid), they appeared to reach termination at the same rate in

| lang. | train. | dev. | test | tags | train. tags |
|-------|--------|------|------|------|-------------|
| eng | 38,219 | 5,527 | 5,462 | 45 | 45 |
| rom | 5,216 | 652 | 652 | 405 | 391 |
| est | 5,183 | 648 | 647 | 413 | 408 |
| cze | 5,402 | 675 | 675 | 955 | 908 |
| fin | 5,043 | 630 | 630 | 2,355 | 2,141 |

Table 1: Overview on data. The training (train.), development (dev.) and test set sizes are given in sentences. The columns titled *tags* and *train. tags* correspond to total number of tags in the data set and number of tags in the training set, respectively.

POS tagging.  Our preliminary experiments using the latest violation updates supported this. Consequently, we employ the early updates.

We also provide results using the CRFsuite toolkit (Okazaki, 2007), which implements a 1st-order CRF model.   To best of our knowledge, CRFsuite is currently the fastest freely available CRF implementation.[3] In addition to the averaged perceptron algorithm (Collins, 2002), the toolkit implements several training procedures (Nocedal, 1980; Crammer et al., 2006; Andrew and Gao, 2007; Mejer and Crammer, 2010; Shalev-Shwartz et al., 2011).  We run CRFsuite using these algorithms employing their default parameters and the feature extraction scheme and stopping criterion described in Section 3.3.  We then report results provided by the most accurate algorithm on each language.

### 3.3  Details on CRF Training and Decoding

While the methods discussed in this work are applicable for $n$th-order CRFs, we employ 1st-order CRFs in order to avoid overfitting the relatively small training sets.

We employ a simple feature set including word forms at position $t-2, \ldots, t+2$, suffixes of word at position $t$ up to four letters, and three orthographic features indicating if the word at position $t$ contains a hyphen, capital letter, or a digit.

All the perceptron variants (PP, PW-PP, 1-best beam search) initialize the model parameters with zero vectors and process the training instances in the order they appear in the corpus. At the end of each pass, we apply the CRFs using the latest averaged parameters (Collins, 2002) to the development set. We assume the algorithms have converged when the model accuracy on development

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[3]See benchmark results at `http://www.chokkan.org/software/crfsuite/benchmark.html`

has not increased during last three iterations. After termination, we apply the averaged parameters yielding highest performance on the development set to test instances.

Test and development instances are decoded using a combination of Viterbi search and the *tag dictionary* approach of Ratnaparkhi (1996). In this approach, candidate tags for known word forms are limited to those observed in the training data. Meanwhile, word forms that were unseen during training consider the full label set.

### 3.4 Software and Hardware

The experiments are run on a standard desktop computer. We use our own C++-based implementation of the methods discussed in Section 2.

## 4 Results

The obtained training times and test set accuracies (measured using accuracy and out-of-vocabulary (OOV) accuracy) are presented in Table 2. The training CPU times include the time (in minutes) consumed by running the perceptron algorithm variants as well as evaluation of the development set accuracy. The column labeled *it.* corresponds to the number of passes over training set made by the algorithms before termination.

We summarize the results as follows. First, PW-PP provided higher accuracies compared to PP on Romanian, Czech, and Finnish. The differences were statistically significant[4] on Czech. Second, while yielding similar running times compared to 1-best beam search, PW-PP provided higher accuracies on all languages apart from Finnish. The differences were significant on Estonian and Czech. Third, while fastest on the Penn Treebank, the CRFsuite toolkit became substantially slower compared to PW-PP when the number of labels were increased (see Czech and Finnish). The differences in accuracies between the best performing CRFsuite algorithm and PP and PW-PP were significant on Czech.

## 5 Conclusions

We presented a heuristic perceptron variant for estimation of CRFs in the spirit of the classic

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[4]We establish significance (with confidence level 0.95) using the standard 1-sided Wilcoxon signed-rank test performed on 10 randomly divided, non-overlapping subsets of the complete test sets.

| method | it. | time (min) | acc. | OOV |
|--------|-----|-----------|------|-----|
| *English* | | | | |
| PP | **9** | 6 | 96.99 | 87.97 |
| PW-PP | 10 | 7 | 96.98 | 88.11 |
| 1-best beam | 17 | 8 | 96.91 | 88.33 |
| Pas.-Agg. | **9** | **1** | **97.01** | **88.68** |
| *Romanian* | | | | |
| PP | 9 | 8 | 96.81 | 83.66 |
| PW-PP | **8** | **7** | 96.91 | 84.38 |
| 1-best beam | 17 | 10 | 96.88 | **85.32** |
| Pas.-Agg. | 13 | 9 | **97.06** | 84.69 |
| *Estonian* | | | | |
| PP | 10 | 8 | **93.39** | 78.10 |
| PW-PP | **8** | **6** | 93.35 | **78.66** |
| 1-best beam | 23 | 15 | 92.95 | 75.65 |
| Pas.-Agg. | 15 | 12 | 93.27 | 77.63 |
| *Czech* | | | | |
| PP | **11** | 26 | 89.37 | 70.67 |
| PW-PP | 16 | 41 | 89.84 | 72.52 |
| 1-best beam | 14 | **19** | 88.95 | 70.90 |
| Pegasos | 15 | 341 | **90.42** | **72.59** |
| *Finnish* | | | | |
| PP | **11** | 58 | 87.09 | 58.58 |
| PW-PP | **11** | **56** | 87.16 | 58.50 |
| 1-best beam | 21 | 94 | **87.38** | **59.29** |
| Pas.-Agg. | 16 | 693 | 87.17 | 57.58 |

Table 2: Results. We report CRFsuite results provided by most accurate algorithm on each language: the *Pas.-Agg.* and *Pegasos* refer to the algorithms of Crammer et al. (2006) and Shalev-Shwartz et al. (2011), respectively.

pseudo-likelihood estimator. The resulting approximative algorithm has a linear time complexity in the label set cardinality and contains only a single hyper-parameter, namely, the number of passes taken over the training data set. We evaluated the algorithm in POS tagging on five languages. Despite its heuristic nature, the algorithm provided competetive accuracies and running times against reference methods.

## Acknowledgements

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# Part-of-Speech Tagging using Conditional Random Fields: Exploiting Sub-Label Dependencies for Improved Accuracy

**Miikka Silfverberg**[a]    **Teemu Ruokolainen**[b]    **Krister Lindén**[a]    **Mikko Kurimo**[b]

[a] Department of Modern Languages, University of Helsinki,
`firstname.lastname@helsinki.fi`

[b] Department of Signal Processing and Acoustics, Aalto University,
`firstname.lastname@aalto.fi`

## Abstract

We discuss part-of-speech (POS) tagging in presence of large, fine-grained label sets using conditional random fields (CRFs). We propose improving tagging accuracy by utilizing dependencies within sub-components of the fine-grained labels. These sub-label dependencies are incorporated into the CRF model via a (relatively) straightforward feature extraction scheme. Experiments on five languages show that the approach can yield significant improvement in tagging accuracy in case the labels have sufficiently rich inner structure.

## 1 Introduction

We discuss part-of-speech (POS) tagging using the well-known conditional random field (CRF) model introduced originally by Lafferty et al. (2001). Our focus is on scenarios, in which the POS labels have a *rich inner structure*. For example, consider

| PRON+1SG | V+NON3SG+PRES | N+SG |
|:---:|:---:|:---:|
| I | like | ham |

where the *compound* labels PRON+1SG, V+NON3SG+PRES, and N+SG stand for pronoun first person singular, verb non-third singular present tense, and noun singular, respectively. Fine-grained labels occur frequently in morphologically complex languages (Erjavec, 2010; Haverinen et al., 2013).

We propose improving tagging accuracy by utilizing dependencies within the *sub-labels* (PRON, 1SG, V, NON3SG, N, and SG in the above example) of the compound labels. From a technical perspective, we accomplish this by making use of the fundamental ability of the CRFs to incorporate arbitrarily defined feature functions. The newly-defined features are expected to alleviate data spar-

sity problems caused by the fine-grained labels. Despite the (relative) simplicity of the approach, we are unaware of previous work exploiting the sub-labels to the extent presented here.

We present experiments on five languages (English, Finnish, Czech, Estonian, and Romanian) with varying POS annotation granularity. By utilizing the sub-labels, we gain significant improvement in model accuracy given a sufficiently fine-grained label set. Moreover, our results indicate that exploiting the sub-labels can yield larger improvements in tagging compared to increasing model order.

The rest of the paper is organized as follows. Section 2 describes the methodology. Experimental setup and results are presented in Section 3. Section 4 discusses related work. Lastly, we provide conclusions on the work in Section 5.

## 2 Methods

### 2.1 Conditional Random Fields

The (unnormalized) CRF model (Lafferty et al., 2001) for a sentence $x = (x_1, \ldots, x_{|x|})$ and a POS sequence $y = (y_1, \ldots, y_{|x|})$ is defined as

$$p(y \mid x; \boldsymbol{w}) \propto \prod_{i=n}^{|x|} \exp\left(\boldsymbol{w} \cdot \boldsymbol{\phi}(y_{i-n}, \ldots, y_i, x, i)\right),$$
(1)

where $n$ denotes the model order, $\boldsymbol{w}$ the model parameter vector, and $\boldsymbol{\phi}$ the feature extraction function. We denote the tag set as $\mathcal{Y}$, that is, $y_i \in \mathcal{Y}$ for $i \in 1 \ldots |x|$.

### 2.2 Baseline Feature Set

We first describe our baseline feature set $\{\phi_j(y_{i-1}, y_i, x, i)\}_{j=1}^{|\phi|}$ by defining *emission* and *transition* features. The emission feature set associates properties of the sentence position $i$ with

the corresponding label as

$$\{\chi_j(x,i)\mathbb{1}(y_i = y_i') \,|\, j \in 1\ldots|\mathcal{X}|\,, \forall y_i' \in \mathcal{Y}\}, \quad (2)$$

where the function $\mathbb{1}(q)$ returns one if and only if the proposition $q$ is true and zero otherwise, that is

$$\mathbb{1}(y_i = y_i') = \left\{ \begin{array}{ll} 1 & \textbf{if}\quad y_i = y_i' \\ 0 & \textbf{otherwise} \end{array} \right. , \quad (3)$$

and $\mathcal{X} = \{\chi_j(x,i)\}_{j=1}^{|\mathcal{X}|}$ is the set of functions characterizing the word position $i$. Following the classic work of Ratnaparkhi (1996), our $\mathcal{X}$ comprises simple binary functions:

1. Bias (always active irrespective of input).

2. Word forms $x_{i-2}, \ldots, x_{i+2}$.

3. Prefixes and suffixes of the word form $x_i$ up to length $\delta_{suf} = 4$.

4. If the word form $x_i$ contains (one or more) capital letter, hyphen, dash, or digit.

Binary functions have a return value of either zero (inactive) or one (active). Meanwhile, the transition features

$$\{\mathbb{1}(y_{i-k} = y_{i-k}') \ldots \mathbb{1}(y_i = y_i') \,| \\ y_{i-k}', \ldots, y_i' \in \mathcal{Y}, \forall k \in 1 \ldots n\} \quad (4)$$

capture dependencies between adjacent labels irrespective of the input $x$.

### 2.2.1 Expanded Feature Set Leveraging Sub-Label Dependencies

The baseline feature set described above can yield a high tagging accuracy given a conveniently simple label set, exemplified by the tagging results of Collins (2002) on the Penn Treebank (Marcus et al., 1993). (Note that conditional random fields correspond to discriminatively trained hidden Markov models and Collins (2002) employs the latter terminology.) However, it does to some extent overlook some beneficial dependency information in case the labels have a rich sub-structure. In what follows, we describe expanded feature sets which explicitly model the sub-label dependencies.

We begin by defining a function $\mathcal{P}(y_i)$ which partitions any label $y_i$ into its sub-label components and returns them in an unordered set. For example, we could define $\mathcal{P}(\text{PRON}+1+\text{SG}) =$

{PRON, 1, SG}. (Label partitions employed in the experiments are described in Section 3.2.) We denote the set of all sub-label components as $\mathcal{S}$.

Subsequently, instead of defining only (2), we additionally associate the feature functions $\mathcal{X}$ with all sub-labels $s \in \mathcal{S}$ by defining

$$\{\chi_j(x,i)\mathbb{1}(s \in \mathcal{P}(y_i)) \,|\, \forall j \in 1\ldots|\mathcal{X}|\,, \forall s \in \mathcal{S}\}, \quad (5)$$

where $\mathbb{1}(s \in \mathcal{P}(y_i))$ returns one in case $s$ is in $\mathcal{P}(y_i)$ and zero otherwise. Second, we exploit *sub-label transitions* using features

$$\{\mathbb{1}(s_{i-k} \in \mathcal{P}(y_{i-k})) \ldots \mathbb{1}(s_i \in \mathcal{P}(y_i)) \,| \\ \forall s_{i-k}, \ldots, s_i \in \mathcal{S}\,, \forall k \in 1\ldots m\}. \quad (6)$$

Note that we define the sub-label transitions up to order $m$, $1 \le m \le n$, that is, an $n$th-order CRF model is not obliged to utilize sub-label transitions all the way up to order $n$. This is because employing high-order sub-label transitions may potentially cause overfitting to training data due to substantially increased number of features (equivalent to the number of model parameters, $|\boldsymbol{w}| = |\boldsymbol{\phi}|$). For example, in a second-order ($n = 2$) model, it might be beneficial to employ the sub-label emission feature set (5) and first-order sub-label transitions while discarding second-order sub-label transitions. (See the experimental results presented in Section 3.)

In the remainder of this paper, we use the following notations.

1. A standard CRF model incorporating (2) and (4) is denoted as CRF($n$,-).

2. A CRF model incorporating (2), (4), and (5) is denoted as CRF($n$,0).

3. A CRF model incorporating (2), (4), (5), and (6) is denoted as CRF($n$,$m$).

### 2.3 On Linguistic Intuition

This section aims to provide some intuition on the types of linguistic phenomena that can be captured by the expanded feature set. To this end, we consider an example on the plural number in Finnish.

First, consider the plural nominative word form *kissat* (*cats*) where the plural number is denoted by the 1-suffix *-t*. Then, by employing the features (2), the suffix *-t* is associated solely with the compound label NOMINATIVE+PLURAL. However, by incorporating the expanded feature set (5), *-t*

will also be associated to the sub-label PLURAL. This can be useful because, in Finnish, also adjectives and numerals are inflected according to number and denote the plural number with the suffix *-t* (Hakulinen et al., 2004, §79). Therefore, one can exploit *-t* to predict the plural number also in words such as *mustat (plural of black)* with a compound analysis ADJECTIVE+PLURAL.

Second, consider the number agreement (congruence). For example, in the sentence fragment *mustat kissat juoksevat (black cats are running)*, the words *mustat* and *kissat* share the plural number. In other words, the analyses of both *mustat* and *kissat* are required to contain the sub-label PLURAL. This short-span dependency between sub-labels will be captured by a first-order sub-label transition feature included in (6).

Lastly, we note that the feature expansion sets (5) and (6) will, naturally, capture any short-span dependencies within the sub-labels irrespective if the dependencies have a clear linguistic interpretation or not.

## 3   Experiments

### 3.1   Data

For a quick overview of the data sets, see Table 1.

**Penn Treebank.** The English Penn Treebank (Marcus et al., 1993) is divided into 25 sections of newswire text extracted from the Wall Street Journal. We split the data into training, development, and test sets using the sections 0-18, 19-21, and 22-24, according to the standardly applied division introduced by Collins (2002).

**Turku Depedency Treebank.** The Finnish Turku Depedendency Treebank (Haverinen et al., 2013) contains text from 10 different domains. The treebank does not have default partition to training and test sets. Therefore, from each 10 consecutive sentences, we assign the 9th and 10th to the development set and the test set, respectively. The remaining sentences are assigned to the training set.

**Multext-East.** The third data we consider is the multilingual Multext-East (Erjavec, 2010) corpus, from which we utilize the Czech, Estonian and Romanian sections. The corpus corresponds to translations of the novel *1984* by George Orwell. We apply the same data splits as for Turku Dependency Treebank.

| lang. | train. | dev. | test | tags | train. tags |
|---|---|---|---|---|---|
| Eng | 38,219 | 5,527 | 5,462 | 45 | 45 |
| Rom | 5,216 | 652 | 652 | 405 | 391 |
| Est | 5,183 | 648 | 647 | 413 | 408 |
| Cze | 5,402 | 675 | 675 | 955 | 908 |
| Fin | 5,043 | 630 | 630 | 2,355 | 2,141 |

Table 1: Overview on data. The training (train.), development (dev.) and test set sizes are given in sentences. The columns titled *tags* and *train. tags* correspond to total number of tags in the data set and number of tags in the training set, respectively.

### 3.2   Label Partitions

This section describes the employed compound label splits. The label splits for all data sets are submitted as data file attachments. All the splits are performed *a priori* to model learning, that is, we do not try to optimize them on the development sets.

The POS labels in the Penn Treebank are split in a way which captures relevant inflectional categories, such as tense and number. Consider, for example, the split for the present tense third singular verb label $\mathcal{P}(\text{VBZ}) = \{\text{VB, Z}\}$.

In the Turku Dependency Treebank, each morphological tag consists of sub-labels marking word-class, relevant inflectional categories, and their respective values. Each inflectional category, such as case or tense, combined with its value, such as nominative or present, constitutes one sub-label. Consider, for example, the split for the singular, adessive noun $\mathcal{P}(\text{N+CASE\_ADE+NUM\_SG}) = \{\text{POS\_N}, \text{CASE\_ADE}, \text{NUM\_SG}\}$.

The labeling scheme employed in the Multext-East data set represents a considerably different annotation approach compared to the Penn and Turku Treebanks. Each morphological analysis is a sequence of feature markers, for example Pw3–r. The first feature marker (P) denotes word class and the rest (w, 3, and r) encode values of inflectional categories relevant for that word class. A feature marker may correspond to several different values depending on word class and its position in the analysis. Therefore it becomes rather difficult to split the labels into similar pairs of inflectional category and value as we are able to do for the Turku Dependency Treebank. Since the interpretation of a feature marker depends on its position in the analysis and the word class, the markers have to be numbered and appended with the

word class marker. For example, consider the split $\mathcal{P}(\text{Pw3–r}) = \{0 : P, 1 : Pw, 2 : P3, 5 : Pr\}$.

### 3.3 CRF Model Specification

We perform experiments using first-order and second-order CRFs with zeroth-order and first-order sub-label features. Using the notation introduced in Section 2, the employed models are CRF(1,-), CRF(1,1), CRF(2,-), CRF(2,0), and CRF(2,1). We do not report results using CRF(2,2) since, based on preliminary experiments, this model overfits on all languages.

The CRF model parameters are estimated using the averaged perceptron algorithm (Collins, 2002). The model parameters are initialized with a zero vector. We evaluate the latest averaged parameters on the held-out development set after each pass over the training data and terminate training if no improvement in accuracy is obtained during three last passes. The best-performing parameters are then applied on the test instances.

We accelerate the perceptron learning using beam search (Zhang and Clark, 2011). The beam width, $b$, is optimized separately for each language on the development sets by considering $b = 1, 2, 4, 8, 16, 32, 64, 128$ until the model accuracy does not improve by at least 0.01 (absolute).

Development and test instances are decoded using Viterbi search in combination with the tag dictionary approach of Ratnaparkhi (1996). In this approach, candidate tags for known word forms are limited to those observed in the training data. Meanwhile, word forms that were unseen during training consider the full label set.

### 3.4 Software and Hardware

The experiments are run on a standard desktop computer (Intel Xeon E5450 with 3.00 GHz and 64 GB of memory). The methods discussed in Section 2 are implemented in C++.

### 3.5 Results

The obtained tagging accuracies and training times are presented in Table 2. The times include running the averaged perceptron algorithm and evaluation of the development sets. The column labeled *it.* corresponds to the number of passes over the training data made by the perceptron algorithm before termination. We summarize the results as follows.

First, compared to standard feature extraction approach, employing the sub-label transition fea-

tures resulted in improved accuracy on all languages apart from English. The differences were statistically significant on Czech, Estonian, and Finnish. (We establish statistical significance (with confidence level 0.95) using the standard 1-sided Wilcoxon signed-rank test performed on 10 randomly divided, non-overlapping subsets of the complete test sets.) This results supports the intuition that the sub-label features should be most useful in presence of large, fine-grained label sets, in which case the learning is most affected by data sparsity.

Second, on all languages apart from English, employing a first-order model with sub-label features yielded higher accuracy compared to a second-order model with standard features. The differences were again statistically significant on Czech, Estonian, and Finnish. This result suggests that, compared to increasing model order, exploiting the sub-label dependencies can be a preferable approach to improve the tagging accuracy.

Third, applying the expanded feature set inevitably causes some increase in the computational cost of model estimation. However, as shown by the running times, this increase is not prohibitive.

## 4 Related Work

In this section, we compare the approach presented in Section 2 to two prior systems which attempt to utilize sub-label dependencies in a similar manner.

Smith et al. (2005) use a CRF-based system for tagging Czech, in which they utilize expanded emission features similar to our (5). However, they do not utilize the full expanded transition features (6). More specifically, instead of utilizing a single chain as in our approach, Smith et al. employ five parallel structured chains. One of the chains models the sequence of word-class labels such as noun and adjective. The other four chains model gender, number, case, and lemma sequences, respectively. Therefore, in contrast to our approach, their system does not capture cross-dependencies between inflectional categories, such as the dependence between the word-class and case of adjacent words. Unsurprisingly, Smith et al. fail to achieve improvement over a generative HMM-based POS tagger of Hajič (2001). Meanwhile, our system outperforms the generative trigram tagger HunPos (Halácsy et al., 2007) which is an im-

| model | it. | time (min) | acc. | OOV. |
|-------|-----|-----------|------|------|
| *English* | | | | |
| CRF(1, -) | 8 | 9 | 97.04 | 88.65 |
| CRF(1, 0) | 6 | 17 | 97.02 | 88.44 |
| CRF(1, 1) | 8 | 22 | 97.02 | 88.82 |
| CRF(2, -) | 9 | 15 | 97.18 | 88.82 |
| CRF(2, 0) | 11 | 36 | 97.17 | 89.23 |
| CRF(2, 1) | 8 | 27 | 97.15 | 89.04 |
| *Romanian* | | | | |
| CRF(1, -) | 14 | 29 | 97.03 | 85.01 |
| CRF(1, 0) | 13 | 68 | 96.96 | 84.59 |
| CRF(1, 1) | 16 | 146 | 97.24 | 85.94 |
| CRF(2, -) | 7 | 19 | 97.08 | 85.21 |
| CRF(2, 0) | 18 | 99 | 97.02 | 85.42 |
| CRF(2, 1) | 12 | 118 | 97.29 | 86.25 |
| *Estonian* | | | | |
| CRF(1, -) | 15 | 28 | 93.39 | 78.66 |
| CRF(1, 0) | 17 | 66 | 93.81 | 80.44 |
| CRF(1, 1) | 13 | 129 | 93.77 | 79.37 |
| CRF(2, -) | 15 | 30 | 93.48 | 77.13 |
| CRF(2, 0) | 13 | 53 | 93.78 | 79.60 |
| CRF(2, 1) | 16 | 105 | 94.01 | 79.53 |
| *Czech* | | | | |
| CRF(1, -) | 6 | 28 | 89.28 | 70.90 |
| CRF(1, 0) | 10 | 112 | 89.94 | 74.44 |
| CRF(1, 1) | 10 | 365 | 90.78 | 76.83 |
| CRF(2, -) | 19 | 91 | 89.81 | 72.44 |
| CRF(2, 0) | 13 | 203 | 90.35 | 76.37 |
| CRF(2, 1) | 24 | 936 | 91.00 | 77.75 |
| *Finnish* | | | | |
| CRF(1, -) | 10 | 80 | 87.37 | 59.29 |
| CRF(1, 0) | 13 | 249 | 88.58 | 63.46 |
| CRF(1, 1) | 12 | 474 | 88.41 | 62.63 |
| CRF(2, -) | 11 | 106 | 86.74 | 56.96 |
| CRF(2, 0) | 13 | 272 | 88.52 | 63.46 |
| CRF(2, 1) | 12 | 331 | 88.68 | 63.62 |

Table 2: Results.

proved open-source implementation of the well-known TnT tagger of Brants (2000). The obtained HunPos results are presented in Table 3.

| | Eng | Rom | Est | Cze | Fin |
|-------|------|------|------|------|------|
| HunPos | 96.58 | 96.96 | 92.76 | 89.57 | 85.77 |

Table 3: Results using a generative HMM-based HunPos tagger of Halacsy et al. (2007).

Ceauşu (2006) uses a maximum entropy Markov model (MEMM) based system for tagging Romanian which utilizes transitional behavior between sub-labels similarly to our feature set (6). However, in addition to ignoring the most in-

formative emission-type features (5), Ceauşu embeds the MEMMs into the tiered tagging framework of Tufis (1999). In tiered tagging, the full morphological analyses are mapped into a coarser tag set and a tagger is trained for this reduced tag set. Subsequent to decoding, the coarser tags are mapped into the original fine-grained morphological analyses. There are several problems associated with this tiered tagging approach. First, the success of the approach is highly dependent on a well designed coarse label set. Consequently, it requires intimate knowledge of the tag set and language. Meanwhile, our model can be set up with relatively little prior knowledge of the language or the tagging scheme (see Section 3.2). Moreover, a conversion to a coarser label set is necessarily lossy (at least for OOV words) and potentially results in reduced accuracy since recovering the original fine-grained tags from the coarse tags may induce errors. Indeed, the accuracy 96.56, reported by Ceauşu on the Romanian section of the Multext-East data set, is substantially lower than the accuracy 97.29 we obtain. These accuracies were obtained using identical sized training and test sets (although direct comparison is impossible because Ceauşu uses a non-documented random split).

## 5 Conclusions

We studied improving the accuracy of CRF-based POS tagging by exploiting sub-label dependency structure. The dependencies were included in the CRF model using a relatively straightforward feature expansion scheme. Experiments on five languages showed that the approach can yield significant improvement in tagging accuracy given sufficiently fine-grained label sets.

In future work, we aim to perform a more fine-grained error analysis to gain a better understanding where the improvement in accuracy takes place. One could also attempt to optimize the compound label splits to maximize prediction accuracy instead of applying a priori partitions.

### Acknowledgements

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