Unsupervised Models for Morpheme Segmentation and Morphology Learning

MATHIAS CREUTZ and KRISTA LAGUS
Helsinki University of Technology

We present a model family called Morfessor for the unsupervised induction of a simple morphology from raw text data. The model is formulated in a probabilistic maximum a posteriori framework. Morfessor can handle highly-inflecting and compounding languages, where words can consist of lengthy sequences of morphemes. A lexicon of word segments, so called *morphs*, is induced from the data. The lexicon stores information about both the usage and form of the morphs. Several instances of the model are evaluated quantitatively in a morpheme segmentation task on different sized sets of Finnish as well as English data. Morfessor is shown to perform very well compared to a widely known benchmark algorithm, in particular on Finnish data.

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1. INTRODUCTION

When constructing a system that is capable of understanding and producing language, a fundamental task is the determination of the basic language units and their relationships. Many practical natural language processing (NLP) problems are best solved using lexical resources, in their simplest form an application-specific vocabulary. For example, in information retrieval the analysis entails collecting a list of words and detecting their association with topics of discussion. Moreover, a vocabulary is essential for obtaining good results in speech recognition.

Words are often thought of as basic units of representation. However, especially in inflecting and compounding languages this view is hardly optimal. For instance, if one treats the following English words ('hand, hands, left-handed') as separate entities, one neglects the close relationships between these words, as well as the relationship of the plural 's' to other plural word forms (e.g., 'heads, arms, fingers'). Overlooking these regularities accentuates data sparsity, which is a serious problem in statistical language modeling.

Authors' address: Helsinki University of Technology, Adaptive Informatics Research Centre, P.O. Box 5400, FIN-02015 HUT, Finland.

According to linguistic theory, morphemes are the smallest meaning-bearing units of language as well as the smallest units of syntax [Matthews 1991]. Every word consists of one or several morphemes; consider for instance the English words 'hand, hand+s, left+hand+ed, finger+s, un+avail+able'. There exist linguistic methods and automatic tools for retrieving morphological analyses for words, e.g., based on the two-level morphology formalism [Koskenniemi 1983]. However, these systems must be tailored separately for each language, which demands a large amount of manual work by experts. Moreover, specific tasks often require specialized vocabularies, which must keep pace with the rapidly evolving terminologies.

If it is possible to discover a morphology automatically from unannotated text, language and task independence are easier to achieve. As we will demonstrate in this work, by observing the language data alone it is possible to come up with a model that captures regularities within the set of observed word forms. If a human were to learn a language in an analogous way, this would correspond to being exposed to a stream of large amounts of language without observing or interacting with the world where this language is produced. This is clearly not a realistic assumption about language learning in humans. However, Saffran et al. [1996] show that adults are capable of discovering word units rapidly in a stream of a nonsense language without any connection to meaning. This suggests that humans do use distributional cues, such as transition probabilities between sounds, in language learning. And these kinds of statistical patterns in language data can be successfully exploited by appropriately designed algorithms.

Based on a comprehensive review of contemporary studies of how children start to acquire language, also Kit [2003] concludes that children certainly make use of statistical cues. Kit further proposes the least-effort principle as a probable underlying approach that is supported by both empirical evidence and theoretical considerations. The least-effort principle corresponds to Occam's razor, which says that among equally performing models one should prefer the smallest one. This can be formulated mathematically using the Minimum Description Length (MDL) principle [Rissanen 1989] or in a probabilistic framework as a maximum a posteriori (MAP) model.

Generally, a system using language benefits from representing as large a vocabulary as possible. However, both humans and artificial systems need to be able to store language economically using limited memory capacity. This is particularly true about small portable devices. For example, if one has 500 000 word forms in a statistical n-gram language model, or essentially the same information using only 20 000 morphemes, considerable improvements in efficiency can be obtained.

In language understanding and generation one must not only represent possible word forms but also their rules of generation in the context of other words. An important consideration is the ability to generate and to recognize unseen word forms and expressions. For example, we would expect a system to be able to handle the word 'shoewiping' when some other related word forms have been observed (e.g., 'shoe, wiped'). If a word-based system has not observed a word, it cannot recognize or generate it. In contrast, a morpheme-based system can generate and recognize a much larger number of different word forms than it has observed.

In this work we describe a general probabilistic model family for morphology induction. The model family that we call *Morfessor* consists of independent components that can be combined in different configurations. We utilize the maximum a posteriori framework for expressing the model optimization criteria.

Morfessor segments the input words into units called *morphs*. A lexicon of morphs is constructed, where information about both the distributional nature (“usage”) and “form” of each morph is stored. Usage relates to the distributional nature of the occurrence of morphs in words. Form corresponds to the string of letters the morph consists of. We experimentally evaluate different instances of the Morfessor model and compare them against a benchmark morphology-learning algorithm [Goldsmith 2001; 2005].

1.1 Structure of the article

Related work on both morphology learning and word segmentation is discussed in Section 2. Moreover, the point of view of applying different mathematical modeling frameworks is also considered.

The Morfessor model family is outlined in Section 3. The components of the model as well as their interpretations in terms of usage and form are discussed in detail. A summary of our previous morphology discovery methods as instances of this general framework is presented in Section 4.

Section 5 exhibits thorough experimental results comparing the different instances of the model with data sets of different sizes, ranging from thousands to millions of words. The results are intended to provide an understanding on how particular components of the general model affect morphology learning. We use an evaluation task that measures segmentation accuracy and coverage of the proposed segmentations against gold standard segmentations for Finnish and English.

Section 6 discusses issues beyond the discovery of morpheme boundaries as well as considers aspects that are not handled by the current model framework. Conclusions are presented in Section 7.

2. RELATED WORK

Unsupervised morphology induction is closely connected with the field of automatic word segmentation, i.e., the segmentation of text without blanks into words (or sometimes morphemes). For example, consider the Chinese and Japanese languages, where text is written without delimiters between words. A first necessary task in the processing of these languages is to determine probable locations of boundaries between words.

In the following, we will discuss a few aspects related to morphology learning and word segmentation. The existing algorithms in these fields include examples from both the supervised and unsupervised machine learning paradigms. We will focus on unsupervised and minimally supervised methods. For a broader overview, which includes work on supervised algorithms, the reader is referred to, e.g., [Goldsmith 2001; Kit et al. 2002].

2.1 Challenges for highly-inflecting and compounding languages

It is common that algorithms designed for morphology learning not only produce a segmentation of words into morphemes, but additionally attempt to discover relationships between words, such as knowledge of which word forms belong to the same inflectional paradigm. These higher-reaching goals are achieved by constraining the model space severely: prior assumptions regarding the inner structure of words (morphotactics) are expressed as strict constraints. Typically, words are restricted to consist of one stem followed by one, possibly empty, suffix as in, e.g., [Déjean 1998; Snover and Brent 2001]. Goldsmith [2001] induces paradigms that he calls signatures. In doing that he also proposes a

Fig. 1. Morpheme segmentation of the Finnish word ‘elämäntapamuutoksilla’ (“with [the] changes of life style”).

elämä	n	tapa	muutoks	i	lla
life	of	style	change	-s	with

recursive structure in which stems can consist of a sub-stem and a suffix. Also prefixes are possible in Goldsmith’s model.

In word segmentation such constraints are inapplicable, because the number of words per sentence can vary greatly and is rarely known in advance. Commonly, algorithms designed for word segmentation utilize very little prior knowledge or assumptions about the syntax of the language. Instead, prior knowledge about typical word length may be applied, and small seed lexicons are sometimes used for bootstrapping. The segmentation algorithms try to identify character sequences that are likely words without consideration of the context in which the words occur (e.g., [Ando and Lee 2000; Yu 2000; Peng and Schuurmans 2001]).

For highly-inflecting and compounding languages such as Finnish both the outlined approaches are problematic. Typically word segmentation algorithms perform on an insufficient level, apparently due to the lack of any notion of morphotactics. On the other hand, typical morphology learning algorithms have problems because the ingrained assumptions they make about word structure are generally wrong (that is, too strict) for Finnish, or for other highly-inflecting or compounding languages. In short, they cannot handle the possibly high number of morphemes per word. A Finnish word can consist of lengthy sequences of alternating stems and suffixes, as in the example in Figure 1. Our attempts at finding a solution to this problem are described in the current paper. Subsets of these results have previously been presented in the articles [Creutz and Lagus 2002; Creutz 2003; Creutz and Lagus 2004; 2005a]. However, the generalized structure and discussion on its components are presented here for the first time.

2.2 General modeling methodologies

There exist some central mathematical frameworks, or modeling methodologies, that can be used for formulating models for morphology learning and word segmentation.

In maximum likelihood (ML) modeling, only the accuracy of the representation of the data is considered when choosing a model. That is, model complexity (i.e., size of the model) is not taken into account. ML is known to lead to overlearning, unless some restrictive model search heuristics or model smoothing is applied. There exist word segmentation and morphology learning algorithms where the complexity of the model is controlled heuristically, e.g., [Ge et al. 1999; Peng and Schuurmans 2001; Kneissler and Klakow 2001; Creutz and Lagus 2004].

Probabilistic maximum a posteriori (MAP) models and equivalently models based on the Minimum Description Length (MDL) principle choose the best model by simultaneously considering model accuracy and model complexity; simpler models are favored over complex ones. This generally improves generalization capacity by inhibiting overlearning. A number of word segmentation and morphology learning algorithms have been formulated either using MDL or MAP, e.g., [de Marcken 1996; Deligne and Bimbot 1997; Kazakov 1997; Brent 1999; Kit and Wilks 1999; Yu 2000; Goldsmith 2001; Snover and Brent 2001; Creutz and Lagus 2002; Creutz 2003]. In these works, the goal is to find the most likely lexicon (model) as well as a likely segmentation of the data. A more elaborate, and a much more computationally intensive way of performing the task would be to use Bayesian model averaging. There instead of choosing one particular model, every possible model among some parameterized set is chosen with a weight that is proportional to the probability of the particular model. However, we are unaware of attempts to use such an approach in this task.

Finite-state automata (FSA) can be used to describe the possible word forms of a language, e.g., in the two-level morphology framework [Koskenniemi 1983]. There exist algorithms that try to learn FSA:s that compactly model the word forms observed in the training data [Johnson and Martin 2003; Goldsmith and Hu 2004]. Also Altun and Johnson [2001] induce a stochastic finite-state automaton describing Turkish morphology, but their method works only in a supervised learning task, that is, they require a segmented, labeled corpus to begin with.

Parallels from the automaton approach can be drawn to methods, inspired by the works of Zellig S. Harris [1955; 1967], where a word or morpheme boundary is suggested at locations where the predictability of the next letter in a letter sequence is low, e.g., [Déjean 1998; Ando and Lee 2000; Adda-Decker 2003; Feng et al. 2004]. If the letter sequences (words or sentences) are sorted into a suffix tree, these “low-predictability locations” correspond to nodes with a high branching factor. The suffix tree could be compressed by merging nodes that have identical continuations, thereby producing a more compact data structure, which is an FSA.

2.3 Learning morphological structure

The model presented in this work provides a good means for the *segmentation* of words into morphemes. Alternatively, the model can be applied to word form *generation*. The rather few restrictions incorporated in the current model makes it a very permissive model of morphology. Such a model predicts a large number of words outside of the observed training corpus. This is desirable behavior, since a successful learning algorithm should be able to generalize to unseen data. However, a permissive model also makes many mistakes. Many alternative approaches to morphology learning focus on the acquisition of more restrictive morphologies, where much fewer words outside of the training corpus are recognized.

Some works discover pairs of related words or pairs of multiword collocations. Jacquemin [1997] discovers morphological variants of multiword collocations, e.g., ‘longitudinal record*ing*’ vs. ‘longitudinal*ly* record*ed*’. The collocations essentially have the same semantics and can be identified through regular suffix patterns, e.g., $\{(\epsilon$, ing), (ly, ed)$\}$. Baroni et al. [2002] and Neuvel and Fulop [2002] propose algorithms that learn similarities in the spelling of word pairs. The discovery of patterns is not restricted to concatenation, but also include, e.g., vowel change such as the German Umlaut: ‘Anschlag’ vs. ‘Anschläge’. Generation takes place by predicting missing word pairs. For instance, the pair ‘receive’ vs. ‘reception’ yields the pair ‘deceive’ vs. ‘deception’ by analogy (where it is assumed that the word ‘deception’ was not in the training set).

Other works aim at forming larger groups of related word forms. Gaussier [1999] learns derivational morphology from inflectional lexicons. Orthographically similar words are clustered into relational families. From the induced word families, derivational rules can be acquired, such as the following French verb-to-noun conversions: ‘produire’ → ‘production’, ‘produire’ → ‘producteur’. Schone and Jurafsky [2000; 2001] make use of a Harris-like algorithm to separate suffixes and prefixes from word stems. Whether two orthographically similar word forms are morphologically related is determined from their context of neighboring words. A semantic representation for a word is obtained from the context using Latent Semantic Analysis (LSA). The semantic properties of a word are assumed to emerge from a large context window, whereas syntactic properties can be determined from a narrow window of the immediate word context. In addition to orthographic, semantic, and syntactic similarity, transitive closure is utilized as a forth component. That is, if ‘conductive’ is related to ‘conduct’ and ‘conductivity’ is related to ‘conductive’, then ‘conductivity’ is related to ‘conduct’.

Yarowsky and Wicentowski [2000] and Yarowsky et al. [2001] discover shared root forms for a group of inflected words. Verbs in numerous languages are studied. Frequency distributions are included as a clue to whether words are related. For instance, the English word ‘singed’ can be discarded as a past tense candidate of ‘to sing’ because ‘singed’ is far too rare. Furthermore, parallel corpora in multiple languages are utilized, and one language can function as a “bridge” for another language. For example, the French verb ‘croire’ can be discovered as the root of ‘croyaient’, since these two forms are linked to the English verb ‘believe’ in a parallel text. A missing link from the resembling verb forms ‘croissant’ and ‘croître’ tells us that these are not likely to be related to ‘croire’. Wicentowski [2004] learns a set of string transductions from inflection-root pairs and uses these to transform unseen inflections to their corresponding root forms. This model, however, is trained in a supervised manner.

A further step consists in inducing complete inflectional paradigms, i.e., discovering sets of stems that can be combined with a particular set of suffixes. Goldsmith [2001] formulates his well-known algorithm Linguistica in an MDL framework, whereas Snover and Brent [2001] and Snover et al. [2002] present a similar, probabilistically formulated, model. These models do not predict any word forms outside of the training data. If the following English verb forms have been observed: ‘talk, talks, talking, walk, walked, walks’, the verbs ‘talk’ and ‘walk’ will go into separate paradigms: ‘talk’ with the suffix set {ϵ, s, ing} and ‘walk’ with the suffix set {ϵ, ed, s}. More general paradigms can be obtained by “collapsing them” together, i.e. clustering them based on context similarity [Hu et al. 2005b]. This model can, in principle, predict the missing verb forms ‘talked’ and ‘walking’.

As mentioned previously in Section 2.1, existing models make the learning of higher-level morphological structure computationally feasible by assuming that a word consists of maximally two, or three, morphemes. In recent work, Goldsmith and Hu [2004] and Hu et al. [2005a] move towards morphologies with a larger number of morphemes per word. A heuristic is described that is capable of learning 3- and 4-state FSA:s that model word forming in Swahili, a language with rich prefixation.

2.4 Composition of meaning and form

A central question regarding morpheme segmentation is the *compositionality* of meaning and form. If the meaning of a word is transparent in the sense that it is the “sum of the meaning of the parts”, then the word can be split into the parts, which are the morphemes, e.g., English ‘foot+print, joy+ful+ness, play+er+s’. However, it is not uncommon that the form does consist of several morphemes, which are the smallest elements of syntax, but the meaning is not entirely compositional, e.g., English ‘foot+man’ (male servant wearing a uniform), ‘joy+stick’ (control device), ‘sky+scrap+er’ (very tall building).

de Marcken [1996] proposes a model for unsupervised language acquisition, in which he defines two central concepts: *composition* and *perturbation*. Composition means that an entry in the lexicon is composed of other entries, e.g., ‘joystick’ is composed of ‘joy’ and ‘stick’. Perturbation means that changes are introduced that give the whole a unique identity, e.g., the meaning of ‘joystick’ is not exactly the result of the composition of the parts. This framework is similar to the class hierarchy of many programming languages, where classes can modify default behaviors that are inherited from superclasses. The more of its properties a lexical parameter inherits from its components, the fewer need to be specified via perturbations.

Among other things, de Marcken applies his model in a task of unsupervised word segmentation of a text, where the blanks have been removed. As a result, hierarchical segmentations are obtained, e.g., for the phrase ‘for the purpose of’: [[f[or]][[t[he]][[[p[ur]][[[po]s] e]][of]]]]. The problem here from a practical point of view is that there is no way of determining which level of segmentation corresponds best to a conventional word segmentation. On the coarsest level the phrase works as an independent “word” (‘forthepurposeof’). On the most detailed level the phrase is shattered into individual letters.

3. FORMULATION OF THE MORFESSOR MODEL STRUCTURE

The determination of a suitable model family, that is, model structure, is of central importance, since it sets a hard constraint on what can be learned in principle. A too restricting model family may exclude all optimal and near-optimal models, making learning a good model impossible, regardless of how much data and computation time is spent. In contrast, a too flexible model family is very hard to learn as it requires impractical amounts of data and computation.

We present Morfessor, a probabilistic model family for morphology learning. The model family consists of a number of distinct components which can be interpreted to encode both syntactic and semantic aspects of morphs, which are word segments discovered from data. Morfessor is a unifying framework that encompasses the particular models introduced earlier in [Creutz and Lagus 2002; Creutz 2003; Creutz and Lagus 2004; 2005a], and also has close connections to models proposed by other researchers. Each of these particular works has brought additional understanding regarding relevant problems and how they can be solved.

This section contains the mathematical formulation of the general model structure along with a discussion of the interpretation of its components. In Section 4 we outline how our earlier models can be seen as particular instances, or subsets, of this model. For a discussion on how to estimate any of the models (i.e., for the details of the model search algorithms), the interested reader is referred to our earlier publications.

3.1 Maximum a posteriori estimate of the overall probability

The task is to induce a model of language in an unsupervised manner from a corpus of raw text. The model of language ($\mathcal{M}$) consists of a morph vocabulary, or a *lexicon of morphs*, and a *grammar*. We aim at finding the optimal model of language for producing a segmentation of the corpus, i.e., a set of morphs that is concise, and moreover gives a concise representation for the corpus. The *maximum a posteriori* (MAP) estimate for the parameters, which is to be maximized, is:

$$\arg\max_{\mathcal{M}} P(\mathcal{M} \,|\, \textit{corpus}) = \arg\max_{\mathcal{M}} P(\textit{corpus} \,|\, \mathcal{M}) \cdot P(\mathcal{M}), \text{ where} \tag{1}$$

$$P(\mathcal{M}) = P(\textit{lexicon}, \textit{grammar}). \tag{2}$$

As can be seen above (Eq. 1), the MAP estimate consists of two parts: the probability of the model of language $P(\mathcal{M})$ and the *maximum likelihood* (ML) estimate of the corpus conditioned on the given model of language, written as $P(\textit{corpus} \,|\, \mathcal{M})$. The probability of the model of language (Eq. 2) is the joint probability of the probability of the induced lexicon and grammar. It incorporates our assumptions of how some features should affect the morphology learning task. This is the *Bayesian* notion of probability, i.e., using probabilities for expressing degrees of prior belief rather than counting relative frequency of occurrence in some empirical test setting.

In the following, we will describe the components of the Morfessor model in greater detail, by studying the representation of the lexicon, grammar and corpus, as well as the components of these.

3.2 Lexicon

The lexicon contains one entry for each distinct morph (morph type) in the segmented corpus. We use the term “lexicon” to refer to an inventory of whatever information one might want to store regarding a set of morphs, including their interrelations.

Suppose that the lexicon consists of M distinct morphs. The probability of coming up with a particular set of M morphs $\mu_1 \ldots \mu_M$ making up the lexicon can be written as:

$$P(\textit{lexicon}) = P(\textit{size}(\textit{lexicon}) = M) \cdot P(\textit{properties}(\mu_1), \ldots, \textit{properties}(\mu_M)) \cdot M!. \quad (3)$$

The product contains three factors: (i) the prior probability that the lexicon contains exactly M distinct morphs, (ii) the joint probability that a set of M morphs, each with a particular set of properties, is created, and (iii) the factor $M!$, which is explained by the fact that there are $M!$ possible orderings of a set of M items and the lexicon is the same regardless of the order in which the M morphs emerged. (It is always possible to afterwards rearrange the morphs into an unambiguously defined order, such as alphabetical order.)

The effect of the first factor, $P(\textit{size}(\textit{lexicon}) = M)$, is negligible, since in the computation of a model involving thousands of morphs and their parameters, one single probability value is of no practical significance. Thus, we have omitted to define a prior distribution for $P(\textit{size}(\textit{lexicon}))$.[1]

The properties of a morph can be divided into information regarding (1) the “usage” and (2) the “form” of the morph:

$$P(\textit{properties}(\mu_i)) = P(\textit{usage}(\mu_i), \textit{form}(\mu_i)). \quad (4)$$

In Section 3.5 we present a set of properties, each of which corresponds to a component of the model, and group them under the usage and form aspects. The purpose of this grouping is to facilitate the understanding of the model: the model itself would be equivalent without it.

3.3 Grammar

Grammar can be viewed to contain information about how language units can be combined. In this work we model a simple morphotactics, that is, word-internal syntax. Instead of estimating the structure of the grammar from data, we currently utilize a specific fixed

[1] If one were to define a proper prior, one possible choice would be Rissanen’s universal prior for positive numbers (see Eq. 14).

structure. Therefore we do not have to calculate the probability of the grammar as a whole, and $P(\mathcal{M})$ in Equation 2 reduces to $P(\textit{lexicon})$.

The fixed structure of the grammar is taken as the following: morphs are generated from a small number of categories, which are *prefix* (PRE), *stem* (STM), *suffix* (SUF), and *non-morpheme* (NON) and will be described more thoroughly below. Between the categories there are transition probabilities, which exhibit the first-order Markov property. Words can consist of any number of morphs, which can be tagged with any categories, with a few restrictions: Suffixes are not allowed in the beginning and prefixes at the end of words. Furthermore, it is impossible to move directly from a prefix to a suffix without passing through another morph.

It is possible for a morph to be assigned different categories in different contexts. The tendency of a morph μ_i to be assigned a particular category C_i, $P(C_i \mid \mu_i)$, (e.g., the probability that the English morph 'ness' functions as a suffix) is derived from the parameters related to the usage of the morph:

$$P(C_i \mid \mu_i) = P(C_i \mid \textit{usage}(\mu_i)). \tag{5}$$

The inverse probability, i.e., the probability of a particular morph when the category is known, is needed for expressing the probability of the segmentation of the corpus. This *emission probability* $P(\mu_i \mid C_i)$ is obtained using Bayes' formula:

$$P(\mu_i \mid C_i) = \frac{P(C_i \mid \mu_i) \cdot P(\mu_i)}{P(C_i)} = \frac{P(C_i \mid \mu_i) \cdot P(\mu_i)}{\sum_{\forall \mu_{i'}} P(C_i \mid \mu_{i'}) \cdot P(\mu_{i'})}. \tag{6}$$

The category-independent probabilities $P(\mu_i)$ are maximum likelihood estimates, i.e., they are computed as the frequency of the morph μ_i in the corpus divided by the total number of morph tokens.

3.4 Corpus

Every word form in the corpus can be represented as a sequence of some morphs that are present in the lexicon. Usually, there are many possible segmentations of a word. In MAP modeling, the one most probable segmentation is chosen. The probability of the corpus, when a particular model of language (lexicon and grammar) and morph segmentation is given, takes the form:

$$P(\textit{corpus} \mid \mathcal{M}) = \prod_{j=1}^{W} \Big[P(C_{j1} \mid C_{j0}) \prod_{k=1}^{n_j} \big[P(\mu_{jk} \mid C_{jk}) \cdot P(C_{j(k+1)} \mid C_{jk}) \big] \Big]. \tag{7}$$

As mentioned in the grammar section above, this is a Hidden Markov Model and it is visualized in Figure 2. The product is taken over the W words in the corpus (token count), which are each split into n_j morphs. The k^{th} morph in the j^{th} word, μ_{jk}, is assigned a category, C_{jk}. The probability that the morph is emitted by the category is written as $P(\mu_{jk} \mid C_{jk})$. There are transition probabilities $P(C_{j(k+1)} \mid C_{jk})$ between the categories, where C_{jk} denotes the category assigned to the k^{th} morph in the word, and $C_{j(k+1)}$ denotes the category assigned to the following, or $(k+1)^{\text{th}}$, morph. The transition probabilities comprise transitions from a special word boundary category (#) to the first morph in the word, as well as the transition from the last morph to a word boundary.

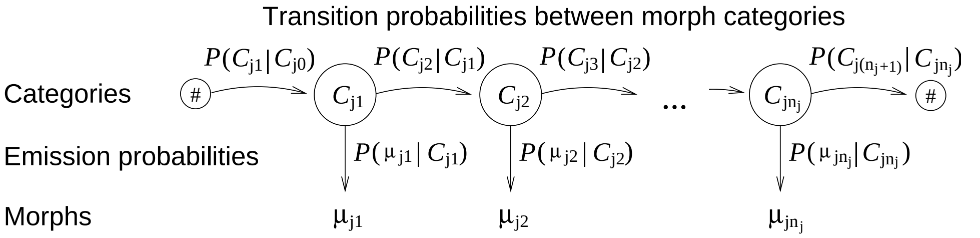


Fig. 2. The HMM model of a word according to Equation 7. The word consists of a sequence of morphs which are emitted from latent categories. For instance, a possible category sequence for the English word 'unavailable' would be 'prefix + stem + suffix' and the corresponding morphs would be 'un + avail + able'.

3.5 Usage and form of morphs

In order to find general patterns of how a morph is used, information is collected about the *distributional nature* of the occurrences of the morph in the segmented corpus. We refer to this distribution as the "usage" of the morph. This includes both properties of the morph itself and properties of the context it typically appears in. The typical usage of the morph can be parameterized and the parameters stored in the lexicon. Which parameter values are likely is determined by probability density functions (pdf:s), which are prior pdf:s in the Bayesian sense and favor solutions that are linguistically motivated. The features that have been used for modeling usage in this work, as well as possible extensions, are described in Section 3.5.2.

By the "form" of a morph we understand the symbolic representation of the morph, i.e., the string of letters it consists of. Different strings have different probabilities, which are determined using a prior probability distribution.

Given this distinction between usage and form, we make the assumption that they are statistically independent:

$$\begin{aligned} &P(\textit{properties}(\mu_1), \ldots, \textit{properties}(\mu_M)) = \\ &\qquad P(\textit{usage}(\mu_1), \ldots, \textit{usage}(\mu_M)) \cdot P(\textit{form}(\mu_1), \ldots, \textit{form}(\mu_M)). \end{aligned} \tag{8}$$

3.5.1 *Form of a morph.* In the current model, we further make the simplifying assumption that the forms of the morphs in the lexicon are independent of each other, thus:

$$P(\textit{form}(\mu_1), \ldots, \textit{form}(\mu_M)) = \prod_{i=1}^{M} P(\textit{form}(\mu_i)). \tag{9}$$

We draw inspiration from de Marcken [1996] in the sense that morphs in the lexicon have hierarchical structure. A morph can either consist of a string of letters or of two submorphs, which can recursively consist of submorphs. The probability of the form of the morph μ_i depends on whether the morph is represented as a string of letters (Eq. 10a) or as the concatenation of two submorphs (Eq. 10b):

$$P(\textit{form}(\mu_i)) =$$
$$\begin{cases} (1 - P(\textit{sub})) \cdot \prod_{j=1}^{\textit{length}(\mu_i)} P(c_{ij}). & \text{(10a)} \\ P(\textit{sub}) \cdot P(C_{i1} \mid \textit{sub}) \cdot P(\mu_{i1} \mid C_{i1}) \cdot P(C_{i2} \mid C_{i1}) \cdot P(\mu_{i2} \mid C_{i2}). & \text{(10b)} \end{cases}$$

$P(\textit{sub})$ is the probability that a morph has substructure, i.e., the morph consists of two submorphs. $P(\textit{sub})$ is estimated from the lexicon by dividing the number of morphs having substructure by the total number of morphs.

In (10a), $P(c_{ij})$ is the probability of the j^{th} letter in the i^{th} morph in the lexicon. The last letter of the morph is the *end-of-morph character*, which terminates the morph. The probability distribution to use for the letters in the alphabet can be estimated from the corpus (or the lexicon).

Equation 10b resembles Equation 7, where the probability of the corpus is given. $P(C_{i1} \,|\, \textit{sub})$ is the probability that the first morph in the substructure is assigned the category C_{i1}. $P(C_{i2} \,|\, C_{i1})$ is the transition probability between the categories of the first and second submorphs. $P(\mu_{i1} \,|\, C_{i1})$ and $P(\mu_{i2} \,|\, C_{i2})$ are the probabilities of the submorphs μ_{i1} and μ_{i2} conditioned on the categories C_{i1} and C_{i2}. The transition and morph emission probabilities are the same as in the probability of the corpus (Eq. 7). An example of concrete substructures are given later (Sec. 4.3, Fig. 4).

3.5.2 *Features related to the usage of a morph.* The set of features that could be used for describing usage is very large: The typical set of morphs that occur in the context of the target morph could be stored. Typical syntactic relations of the morph with other morphs could be included. The size of the context could vary from very limited to large and complex. A complex context might reveal different aspects of the usage of the morph, from fine-grained syntactic categories to broader semantic, pragmatic or topical distinctions. One might even use information from multimodal contexts (e.g., images, sounds) for grounding morph *meaning* to perceptions of the world. This reasoning relies on the philospohical view that the meaning of linguistic units (e.g., morphs) is reflected directly in how they are used.

However, in this work only a very limited set of features is used, and only based on information contained in word lists. As properties of the morph itself, we count the *frequency* of the morph in the segmented corpus and the *length* in letters of the morph. As “distilled” properties of the context the morph occurs in, we consider the intra-word *right* and *left perplexity*[2] of the morph.

Using the above features the probability of the usages of the morphs in the lexicon becomes:

$$P(\textit{usage}(\mu_1), \ldots, \textit{usage}(\mu_M)) = \\ P(\textit{freq}(\mu_1), \ldots, \textit{freq}(\mu_M)) \cdot \prod_{i=1}^{M} \big[P(\textit{length}(\mu_i)) \cdot P(\textit{right-ppl}(\mu_i)) \cdot P(\textit{left-ppl}(\mu_i))\big]. \tag{11}$$

Due to practical considerations in the current implementation, we have assumed that the length, right and left perplexity of a morph are independent of the corresponding values of other morphs. In contrast, the frequencies of the morphs are given as a joint probability, that is, there is one single probability for an entire morph frequency distribution. The probability distributions have been chosen due to their generality and simplicity. In a more sophisticated model formulation, one could attempt to model dependencies between morphs and their features, such as the general tendency of frequent morphs to be rather short.

Next, we describe the individual features and the prior probability distributions that are

[2] Perplexity, a function of entropy, describes how predictable the context is given this morph.

used for the range of possible values of these features. We conclude the treatment of morph usage by reporting how the usage of a morph translates into category membership probabilities in the current grammar. We stress that this particular grammar, as well as the set of features used, is only one possible solution among a large number of alternatives.

3.5.2.1 *Frequency.* Frequent and infrequent morphs generally have different semantics. Frequent morphs can be function words and affixes as well as common concepts. The meaning of frequent morphs is often ambiguous as opposed to rare morphs, which are predominantly content words.

The knowledge of the frequency of a morph is required for calculating the value of $P(\mu_i)$ in Equation 6. The probability that a particular frequency distribution emerges is defined by the following prior probability:

$$P(\mathit{freq}(\mu_1), \ldots, \mathit{freq}(\mu_M)) = 1/\binom{N-1}{M-1} = \frac{(M-1)!(N-M)!}{(N-1)!}, \qquad (12)$$

where N is the total number of morph *tokens* in the corpus, which equals the sum of the frequencies of the M morph *types* that make up the lexicon. Equation 12 is derived from combinatorics: As there are $\binom{N-1}{M-1}$ ways of choosing M positive integers that sum up to N, the probability of one particular frequency distribution of M frequencies summing to N is $1/\binom{N-1}{M-1}$.

3.5.2.2 *Length.* We assume that the length of a morph affects the probability of whether the morph is likely to be a stem or belong to another morph category. Stems often carry semantic (as opposed to syntactic) information. As the set of stems is very large in a language, stems are not likely to be very short morphs, because they need to be distinguishable from each other.

The length of a morph can be deduced from its form if an end-of-morph character is used (see Section 3.5.1). However, the consequence of such an approach is that the probability of observing a morph of a particular length decreases *exponentially* with the length of the morph, which is clearly unrealistic. Instead of using an end-of-morph marker, one can explicitly model morph length with more realistic prior probability distributions. A *Poisson distribution* can be justified when modeling the length distributions of word and morph tokens, e.g., [Nagata 1997], but for morph types (i.e., the set of morphs in the lexicon) a *gamma distribution* seems more appropriate [Creutz 2003].

$P(\mathit{length}(\mu_i))$ in Equation 11 assumes values from a gamma distribution if such is used as a prior for morph length. Otherwise, if morph length is modeled implicitly by using an end-of-morph marker, $P(\mathit{length}(\mu_i))$ is superfluous.

3.5.2.3 *Intra-word right and left perplexity.* The left and right perplexity give a very condensed image of the immediate context a morph typically occurs in. Perplexity serves as a measure for the predictability of the preceding or following morph.

Grammatical affixes mainly carry syntactic information. They are likely to be common "general-purpose" morphs that can be used in connection with a large number of other morphs. We assume that a morph is likely to be a prefix if it is difficult to predict what the following morph is going to be. That is, there are many possible right contexts of the morph and the right perplexity is high. Correspondingly, a morph is likely to be a suffix if it is difficult to predict what the preceding morph can be and the left perplexity is high.

The right perplexity of a target morph μ_i is calculated as:

$$\textit{right-ppl}(\mu_i) = \Big[\prod_{\nu_j \,\in\, \text{right-of}(\mu_i)} P(\nu_j \,|\, \mu_i) \Big]^{-\frac{1}{f_{\mu_i}}}. \tag{13}$$

There are f_{μ_i} occurrences of the target morph μ_i in the corpus. The morph tokens ν_j occur to the right of, immediately following, the occurrences of μ_i. The probability distribution $P(\nu_j \,|\, \mu_i)$ is calculated over all such ν_j. Left perplexity can be computed analogously.[3]

As a reasonable probability distribution over the possible values of right and left perplexity, we use *Rissanen's universal prior* for positive numbers ([Rissanen 1989]):[4]

$$P(n) \approx 2^{-\log_2 c - \log_2 n - \log_2 \log_2 n - \log_2 \log_2 \log_2 n - \ldots}, \tag{14}$$

where the sum includes all positive iterates, and c is a constant, about 2.865. To obtain $P(\textit{right-ppl}(\mu_i))$ and $P(\textit{left-ppl}(\mu_i))$, the variable n is substituted by the appropriate value, $\textit{right-ppl}(\mu_i)$ or $\textit{left-ppl}(\mu_i)$

3.5.3 *Category membership probabilities.* In the grammar, the tendency of a morph to be assigned a particular category (PRE, STM, SUF, or NON) is determined by the usage (distributional nature) of the morph (Equation 5). The exact relationship,

$$P(C_i \,|\, \textit{usage}(\mu_i)) = P(C_i \,|\, \textit{freq}(\mu_i), \textit{length}(\mu_i), \textit{right-ppl}(\mu_i), \textit{left-ppl}(\mu_i)), \tag{15}$$

could probably be learned purely from the data, but currently we use a fixed scheme, involving a few adjustable parameters.

We obtain a measure of *prefix-likeness* by applying a graded threshold realized as a sigmoid function to the right perplexity of a morph (see Figure 3a):

$$\textit{prefix-like}(\mu_i) = \big(1 + \exp[-a \cdot (\textit{right-ppl}(\mu_i) - b)]\big)^{-1}. \tag{16}$$

The parameter b is the perplexity threshold, which indicates the point where a morph μ_i is as likely to be a prefix as a non-prefix. The parameter a governs the steepness of the sigmoid. The equation for suffix-likeness is identical except that left perplexity is applied instead of right perplexity (Fig. 3b).

As for stems, we assume that the *stem-likeness* of a morph correlates positively with the *length* in letters of the morph. A sigmoid function is employed as above, which yields:

$$\textit{stem-like}(\mu_i) = \big(1 + \exp[-c \cdot (\textit{length}(\mu_i) - d)]\big)^{-1}. \tag{17}$$

where d is the length threshold and c governs the steepness of the curve (Fig. 3c).

Prefix-, suffix- and stem-likeness assume values between zero and one, but they are not probabilities, since they usually do not sum up to one. A proper probability distribution is obtained by first introducing the *non-morpheme* category, which corresponds to cases where *none* of the proper morph classes is likely. Non-morphemes are typically short,

[3] In fact, the best results are obtained when only context morphs ν_j that are longer than three letters are included in the perplexity calculation. This means that the right and left perplexity are mainly estimates of the predictability of the *stems* that can occur in the context of a target morph. Including shorter morphs seems to make the estimates less reliable, because of the existence of non-morphemes (noise morphs).

[4] Actually Rissanen defines his universal prior over all *non-negative* numbers and he would write $P(n-1)$ on the left side of the equation. Since the lowest possible perplexity is one, we do not include zero as a possible value in our formula.

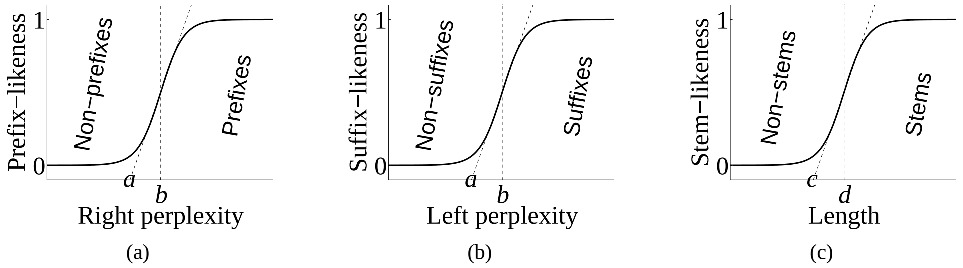


Fig. 3. Sketch of sigmoids, which express our prior belief of how the right and left perplexity as well as the length of a morph affects its tendency to function as a prefix, suffix, or stem.

like the affixes, but their right and left perplexity are low, which indicates that they do not occur in a sufficient number of different contexts in order to qualify as a pre- or suffix. The probability that a segment is a non-morpheme (NON) is:

$$P(\text{NON} \mid \mu_i) = [1 - \textit{prefix-like}(\mu_i)] \cdot [1 - \textit{suffix-like}(\mu_i)] \cdot [1 - \textit{stem-like}(\mu_i)]. \qquad (18)$$

Then the remaining probability mass is distributed between prefix, stem and suffix, e.g.:

$$P(\text{PRE} \mid \mu_i) = \frac{\textit{prefix-like}(\mu_i)^q \cdot [1 - P(\text{NON} \mid \mu_i)]}{\textit{prefix-like}(\mu_i)^q + \textit{stem-like}(\mu_i)^q + \textit{suffix-like}(\mu_i)^q}. \qquad (19)$$

The exponent q affects the normalization. High values of q produce spiky distributions (“winner-take-all effect”), whereas low values produce flatter distributions. We have tested the values $q = 1$ and $q = 2$.

As mentioned in Section 3.5.2.1, the frequency of a morph could possibly be used for distinguishing between “semantic” morphs (stems) and “grammatical” morphs (affixes). In the current scheme, the frequency *as such* is only used for computing the category-independent probabilities $P(\mu_i)$ (Eq. 6). Nonetheless, right and left perplexity are indirect measures of frequency, because a high frequency is a precondition for a high perplexity.

There is a similar idea of using the features frequency, mutual information and left and right entropy in the induction of a Chinese dictionary from an untagged text corpus [Chang et al. 1995]. There, the features are applied in classifying character sequences as either words or non-words, which resembles our morpheme categories and the non-morpheme category. In another work, [Feng et al. 2004], a somewhat simpler feature called accessor variety was used in order to discover words in Chinese text. These features are not new within the field of word segmentation. Already in the pioneering work of Harris [1955] something very akin to “accessor variety” was introduced. Entropy was explored in a Harrisian approach to the segmentation of English words by Hafer and Weiss [1974]. However, in Morfessor, perplexity is not utilized to discover potential morph boundaries, but to assign potential grammatical categories to suggested morphs.

4. MODEL VARIANTS

Our earlier work can be seen as instances of the general Morfessor model, since each of the previous models implements a subset of the components of Morfessor. These models and their central properties are summarized in Table I.

The widely known benchmark, John Goldsmith’s algorithm Linguistica [Goldsmith 2001;

2005], is also included in the comparison even though it does not fit entirely into the Morfessor model family.

4.1 Baseline and Baseline-Length

The *Morfessor Baseline* model was originally presented as the "Recursive MDL model" in [Creutz and Lagus 2002]. The formulation followed from the Minimum Description Length (MDL) principle in a mathematically simplified way. In the Baseline, no context sensitivity is modeled, which corresponds to having only one morph category in the HMM in the grammar. The only feature related to morph usage that is taken into account is morph frequency. The form of the morph is flat, which means that a morph always consists of a string of letters and never has substructure. The Baseline model can be trained on a collection of either *word tokens* or *word types*. The former corresponds to a *corpus*, a piece of text, where words can occur many times. The latter corresponds to a *corpus vocabulary*, where only one occurrence of every distinct word form in the corpus has been listed. These two different types of data lead to different morph segmentations.

The choice of the term "baseline" signals that this model is indeed very simple. In essence, words are split into strings that occur frequently within the words in the corpus, without consideration of the intra-word context in which these segments occur. The more elaborate category-based Morfessor models make use of the Baseline algorithm in order to produce an initial segmentation, which is then refined.

Morfessor Baseline-Length is a slight modification of the model introduced in [Creutz 2003]. It is identical to the Baseline except that a gamma distribution is utilized for modeling morph length. Compared to the Baseline, the Baseline-Length algorithm performs better in a morpheme segmentation task, especially on small amounts of data, but the difference diminishes when the amount of data is increased.

Software implementing the Morfessor Baseline model variants is publicly available[5] under the GNU General Public License. User's instructions are provided in a technical report [Creutz and Lagus 2005b], which further describes the models and the search algorithm used. In brief, the search takes place as follows: The word forms in the corpus are processed, one at a time. First, the word as a whole is considered as a morph to be added to the lexicon. Then, every possible split of the word into two substrings is evaluated. The split (or no split) yielding the highest probability is selected. In case of a split, splitting of the two parts continues recursively and stops when no more gains can be obtained. All words in the corpus are reprocessed until convergence of the overall probability.

The advancement of the search algorithm can be characterized as follows: In order to split a word into two parts, the algorithm must recognize at least one of the parts as a morph. Initially, all entire word forms are considered potential morphs. Since many word stems occur in isolation as entire words (e.g., English 'match'), the algorithm begins to discover suffixes and prefixes by splitting off the known stems from longer words (e.g., 'match+es, match+ing, mis+match'). The newly discovered morphs can in turn be found in words where none of the parts occur in isolation (e.g., 'invit+ing'). As a result of iterating this top-down splitting, the words in the corpus are gradually split down into shorter morphs.[6]

[5] `http://www.cis.hut.fi/projects/morpho/`

[6] Other search strategies could be explored in the future, especially when dealing with languages where free stems are rare, such as Latin (e.g., 'absurd+us, absurd+a, absurd+um, absurd+ae, absurd+o', etc.). However, initial experiments on Latin suggest that also here the current search algorithm manages to get a grip on the

Table I. Summary of some properties of the morphology learning algorithms. In the "Optim." column the nature of the optimization task is indicated. Context sensitivity ("Ctxt-sens.") implies that the position in a word affects the probability of a morph, i.e., some notion of morphotactics is included in the model. The "Usage" column lists the features of morph usage that are accounted for in the form of explicit prior distributions in the probability of the lexicon: frequency ("F"), gamma distribution for morph length ("G"), right ("R") and left ("L") perplexity. The structure of the form of morphs is given in the "Form" column. The "Train" column tells whether the model is trained on a corpus ("tok": word token collection) or corpus vocabulary ("typ": word type collection). The "Long seq." column signals whether the model in question is suitable for morphologies where words can consist of lengthy sequences of morphemes.

Model name	Optim.	Ctxt-sens.	Usage	Form	Train	Long seq.
Baseline	MAP	no	F	flat	tok & typ	yes
Baseline-Length	MAP	no	FG	flat	tok & typ	yes
Categories-ML	ML	yes	FGRL	flat	typ	yes
Categories-MAP	MAP	yes	FGRL	hierar.	tok (& typ)	yes
Linguistica	MAP	yes	–	signat.	typ (& tok?)	no

Both Baselines produce segmentations that are closer to a linguistic morpheme segmentation when trained on a word type collection instead of a word token collection. The use of word types means that all information about word frequency in the corpus is lost. If we are interested in drawing parallels to language processing in humans, this is an undesirable property, because word frequency seems to play an important role in human language processing. Baayen and Schreuder [2000] refer to numerous psycholinguistic studies that report that high-frequency words are responded to more quickly and accurately than low-frequency words in various experimental tasks. This effect is obtained regardless whether the words have compositional structure or not (and both for regular derived and inflected words). Note, however, that these findings may not apply to all linguistic tasks. When test persons were exposed to word forms that were ungrammatical in context, high-frequency regular word forms seemed to be processed as if they were compositional rather than unanalyzed wholes [Allen et al. 2003].

4.2 Categories-ML

The *Morfessor Categories-ML* model has been presented in [Creutz and Lagus 2004]. The model is a maximum likelihood (ML) model that is applied for reanalyzing a segmentation produced by the Baseline-Length algorithm. The morphotactics of the full Morfessor model is used in Categories-ML and all four usage features are included. However, the computation of the category membership probabilities (Section 3.5.3) is only utilized for initializing a category tagging of the morph segmentation obtained from Baseline-Length. Emission probabilities (Equation 6) are then obtained as maximum likelihood estimates from the tagging.

The size of the morph lexicon is not taken into account directly in the calculation of the overall probability, but some heuristics are applied. If a morph in the lexicon consists of other morphs that are present in the lexicon (e.g., 'seemed = seem+ed'), the most probable split (essentially according to Eq. 10b) is selected and the redundant morph is removed. A split into non-morphemes is not allowed, however. If on the contrary, a word has been shattered into many short fragments, these are removed by joining them with their neighboring morphs, which hopefully creates a proper morph (e.g., 'flu+s+ter+ed'

affixes and stems, as the result of a long "chain reaction".

becomes ‘fluster+ed’). This takes place by joining together non-morphemes with their shortest neighbors, until the resulting morph can qualify as a stem, which is determined by Equation 17. The Categories-ML algorithm operates on data consisting of word types.

4.3 Categories-MAP

The latest model, *Categories-MAP*, was introduced in [Creutz and Lagus 2005a]. It is the most extensive model and its formulation is the complete structure presented in Section 3.

The search for the most probable Categories-MAP segmentation takes place using a greedy search algorithm. In an attempt to avoid local maxima of the overall probability function, steps of resplitting and rejoining morphs are alternated; see [Creutz and Lagus 2005a] for details: (i) initialization of a segmentation using Baseline-Length, (ii) splitting of morphs, (iii) joining of morphs using a bottom-up strategy, (iv) resplitting of morphs, (v) resegmentation of the corpus using the Viterbi algorithm and re-estimation of probabilities until convergence, (vi) repetition of Steps (iii)–(v) once.

Figure 4 shows hierarchical representations obtained by Categories-MAP for the Finnish word ‘oppositiokansanedustaja’ (“member of parliament of the opposition”) and the English word ‘straightforwardness’. The Categories-MAP model utilizes information about word frequency: The English word has been frequent enough in the corpus to be included in the lexicon as an entry of its own. The Finnish word has been less common and is split into ‘oppositio’ (“opposition”) and ‘kansanedustaja’ (“member of parliament”), which are two separate entries in the lexicon induced from the Finnish corpus. Frequent words and word segments can thus be accessed directly, which is economical and fast. At the same time, the inner structure of the words is retained in the lexicon, because the morphs are represented as the concatenation of other (sub)morphs, which are also present in the lexicon: The Finnish word can be bracketed as [op positio][[[kansa n] edusta] ja] and the English word as [[straight [for ward]] ness].

Additionally, every morph is tagged with a category, which is the most likely category for that morph in that context. Not all morphs in the lexicon need to be “morpheme-like” in the sense that they represent a meaning. Some morphs correspond more closely to syllables and other short fragments of words. The existence of these non-morphemes (NON) makes it possible to represent some longer morphs more economically, e.g., the Finnish ‘oppositio’ consists of ‘op’ and ‘positio’ (“position”), where ‘op’ has been tagged as a non-morpheme and ‘positio’ as a stem. Sometimes this helps against the oversegmentation of rather rare words. When for instance, a new name must be memorized, it can be constructed from shorter familiar fragments. This means that a fewer number of observations of this name in the corpus suffice for the name to be added as a morph to the lexicon compared to a situation, where the name would need to be memorized letter by letter. For instance, in one of the English experiments the name ‘Zubovski’ occurred twice in the corpus and was added to the morph lexicon as ‘zubov/STM + ski/NON’. One might draw a parallel from the non-morphemes in the Categories-MAP model to findings within psycholinguistic research. McKinnon et al. [2003] suggest that morphological decomposition and representation extend to non-productive morphemes, such as ‘-ceive, -mit’, and ‘-cede’ in English words, e.g., ‘conceive, permit, recede’.

4.3.1 *Using Categories-MAP in a morpheme segmentation task.* In the task of morpheme segmentation, the described data structure is very useful. While de Marcken (Section 2.4) had no means of knowing which level of segmentation is the desired one, we can

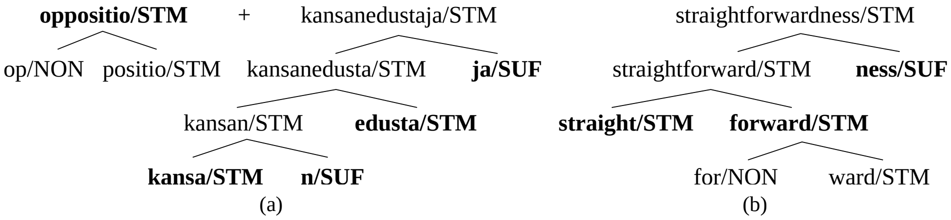


Fig. 4. The hierarchical segmentations of (a) the Finnish word 'oppositiokansanedustaja' (MP of the opposition) and (b) the English word 'straightforwardness' (obtained by the Categories-MAP model for the largest data sets). The finest resolution that does not contain non-morphemes has been identified with boldface.

expand the hierarchical representation to the *finest resolution that does not contain non-morphemes*. In Figure 4 this level has been indicated using a bold-face font. The Finnish word is expanded to 'oppositio + kansa + n + edusta + ja' (literally "opposition + people + of + represent + -ative"). The English word is expanded into 'straight + forward + ness'. The morph 'forward' is not expanded into 'for + ward', although this might be appropriate, because 'for' is tagged as a non-morpheme in the current context.

4.4 Linguistica

The model of Linguistica is formulated in an MDL framework that is equivalent to a MAP model. In the Linguistica algorithm, a morphotactics is implemented, where words are assumed to consist of a stem, optionally preceded by a prefix and usually followed by a suffix. The stem can recursively consist of a substem and a succeeding suffix. This structure is less general than the one used in Morfessor, because Linguistica does not allow consecutive stems (as in, e.g., 'coast+guard+s+man'). Thus, morphologies involving compounding cannot be modeled satisfactorily.

Linguistica groups stems and suffixes into collections called signatures ("signat." in the "Form" column in Table I), which can be thought of as inflectional paradigms: a certain set of stems goes together with a certain set of suffixes. Words will be left unsplit unless the potential stem and suffix fit into a signature. Linguistica is trained on a word type collection, but it seems that word token collections could be used as well.

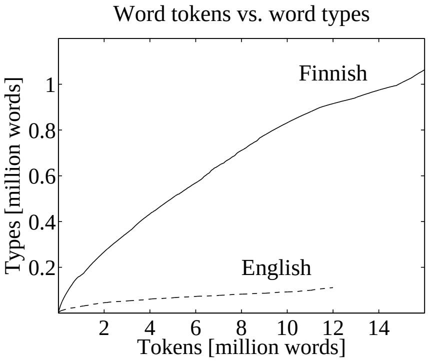
5. EXPERIMENTS

Careful evaluation of any proposed method is essential. Depending on the goal, the evaluation could be carried out directly in some NLP task, such as speech recognition. However, as the performance in such a task depends on many issues and not only on the morphs, it is also useful to evaluate the morph segmentation directly.

In the current paper, the discussed methods are evaluated in a *linguistic morpheme segmentation task*. The goal is to find the locations of morpheme boundaries as accurately as possible. Experiments are performed on Finnish and English corpora, and on data sets of different sizes. As a gold standard for the desired locations of the morpheme boundaries, *Hutmegs* is used (see Section 5.2). Hutmegs consists of fairly accurate conventional linguistic morpheme segmentations for a large number of word forms.

word tokens	Finnish word types	English word types
10 000	5 500	2 400
50 000	20 000	7 200
250 000	65 000	17 000
12 000 000	–	110 000
16 000 000	1 100 000	–

(a)



(b)

Fig. 5. (a) Sizes of the test data subsets used in the evaluation. (b) Curves of the number of word types observed for growing portions of the Finnish and English test sets.

5.1 Finnish and English data sets

The Finnish corpus consists of news texts from the CSC (The Finnish IT Center for Science)[7] and the Finnish News Agency (STT). The corpus contains 32 million words. It has been divided into a development set and a test set, each containing 16 million words.

For experiments on English we use a collection of texts from the Gutenberg project (mostly novels and scientific articles)[8], and a sample from the Gigaword corpus and the Brown corpus[9]. The English corpus contains 24 million words. It has been divided into a development and a test set, each consisting of 12 million words. The *development sets* are utilized for optimizing the algorithms and for selecting parameter values. The *test sets* are used solely in the final evaluation.

What is often overlooked is that a comparison of different algorithms on one single data set size does not give a reliable picture of how the algorithms behave when the amount of data changes. Therefore, we evaluate our algorithms with increasing amounts of test data. The amounts in each subset of the test set are shown in Figure 5a, both as number of word tokens (words of running text) and number of word types (distinct word forms). Figure 5b further shows how the number of word types grows as a function of the number of word tokens for the Finnish and English test sets. As can be seen, for Finnish the number of types grows fast when more text is added, i.e., many new word forms are encountered. In contrast, with English text, a larger proportion of the words in the added text has been observed before.

5.2 Morphological gold standard segmentation

The Helsinki University of Technology Morphological Evaluation Gold Standard (*Hutmegs*) [Creutz and Lindén 2004] contains morpheme segmentations for 1.4 million Finnish word forms and 120 000 English word forms. Hutmegs is based on the two-level morphological analyzer FINTWOL for Finnish [Koskenniemi 1983] and the CELEX database for

[7] `http://www.csc.fi/kielipankki/`

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

[9] The Gigaword sample and the Brown corpus are available at the Linguistic Data Consortium: `http://www.ldc.upenn.edu/`.

English [Baayen et al. 1995]. These existing resources provide a morphological analysis of words, but no surface-level segmentation. For instance, the English word 'bacteriologist' yields the analysis 'bacterium+ology+ist'. The main additional work related to the creation of Hutmegs consists in the semi-automatic production of surface-level, or allomorph, segmentations (e.g., 'bacteri+olog+ist'). Hereby, Hakulinen [1979] has been used as an authoritative guideline for the Finnish morphology and Quirk et al. [1985] for the English morphology. Both inflectional and derivational morphemes are marked in the gold standard.

The Hutmegs package is publicly available on the Internet[10]. For full access to the Finnish morpheme segmentations, an inexpensive license must additionally be purchased from Lingsoft, Inc.[11] Similarly, the English CELEX database is required for full access to the English material[12].

As there can sometimes be many plausible segmentations of a word, Hutmegs provides several alternatives when appropriate, e.g., English 'evening' (time of day) vs. 'even+ing' (verb). There is also an option for so called "fuzzy" boundaries in the Hutmegs annotations, which we have chosen to use. Fuzzy boundaries are applied in cases where it is inconvenient to define one exact transition point between two morphemes. For instance, in English, the stem-final 'e' is dropped in some forms. Here we allow two correct segmentations, namely the traditional linguistic segmentation in 'invite, invite+s, invit+ed' and 'invit+ing', as well as the alternative interpretation, where the 'e' is considered part of the suffix, as in: 'invit+e, invit+es, invit+ed' and 'invit+ing'.[13] In the former case, there are two allomorphs (realization variants) of the stem ('invite' and 'invit'), and one allomorph for the suffixes. In the latter case, there is only one allomorph of the stem ('invit'), whereas there are two allomorphs of the third person present tense ('-s' and '-es') and an additional infinitive ending ('-e'). Since there are a much greater number of different stems than suffixes in the English language, the latter interpretation lends itself to more compact concatenative models of morphology.

5.3 Evaluation measures

As evaluation measures, we use *precision* and *recall* on discovered morpheme boundaries. Precision is the proportion of correctly discovered boundaries among all discovered boundaries by the algorithm. Recall is the proportion of correctly discovered boundaries among all correct boundaries. A high precision thus tells us that when a morpheme boundary is suggested, it is probably correct, but it does not tell us the proportion of missed boundaries. A high recall tells us that most of the desired boundaries were indeed discovered, but it does not tell us how many incorrect boundaries were suggested as well.

In order to get a comprehensive idea of the performance of a method, both measures must be taken into account. A measure that combines precision and recall is the *F-measure*,

[10] `http://www.cis.hut.fi/projects/morpho/`

[11] `http://www.lingsoft.fi`

[12] The CELEX databases for English, Dutch and German are available at the Linguistic Data Consortium: `http://www.ldc.upenn.edu/`.

[13] Note that the possible segmentation 'invite+d' is *not* considered correct, due to the fact that there is no indication that the regular past tense ending '-ed' ever loses its 'e', whereas the preceding stem unquestionably does so, e.g., in 'inviting'.

which is the harmonic mean of the two:

$$\textit{F-Measure} = 1/[\frac{1}{2}(\frac{1}{\textit{Precision}} + \frac{1}{\textit{Recall}})]. \tag{20}$$

We compare performances using all three measures.

Furthermore, the evaluation measures can be computed either using word tokens or word types. If the segmentation of word tokens is evaluated, frequent word forms will dominate in the result, because every occurrence (of identical segmentations) of a word is included. If, instead, the segmentation of word types is evaluated, every distinct word form, frequent or rare, will have equal weight. When inducing the morphology of a language, we consider all word forms to be as important regardless of their frequency. Therefore, in this paper, precision and recall for word types is reported.

For each of the data sizes 10 000, 50 000, and 250 000 words, the algorithms are run on five separate subsets of the test data, and the average results are reported. Furthermore, statistical significance of the differences in performance have been assessed using T-tests. The largest data sets, 16 million words (Finnish) and 12 million words (English) are exceptions, since they contain all available test data, which constrains the number of runs to one.

5.4 Methods to be evaluated

We report experiments on the following methods from the Morfessor family: Baseline-Length, Categories-ML and Categories-MAP (see Table I for a concise description). The Baseline-Length model was trained on a collection of word types. Parameter values related to the priors of the category models (a, b, c, d, and q in Equations 16, 17 and 19) were determined from the development set. The model evaluation was performed using independent test sets.

In addition, we benchmark against ‘Linguistica’ [Goldsmith 2001; 2005][14]. In the Linguistica algorithm, we used the commands ‘Find suffix system’ and ‘Find prefixes of suffixal stems’. We interpreted the results in two ways: (i) to allow a word to be segmented into a maximum of three segments: an optional prefix, followed by a stem, followed by an optional suffix; (ii) to decompose stems that consist of a substem and a suffix, which makes it possible for a word to be segmented into more than three segments. The former solution (i) surprisingly produced better results, and thus these results are reported in this work.

5.5 Results

Figures 6–8 depict the morph splitting performance of the evaluated methods in the Finnish and English morph segmentation tasks. The F-measures shown in Figure 6 allow for a direct comparison of the methods, whereas the precisions in Figure 7 and the recalls in Figures 8 shed more light on the particular strengths and weaknesses. Furthermore, some examples of the segmentations produced are listed in Tables II and III.

We will now briefly comment on the performance of each method in relation to the other methods.

[14] We have used the December 2003 version of the Linguistica program that is publicly available on the Internet `http://humanities.uchicago.edu/faculty/goldsmith/Linguistica2000/`.

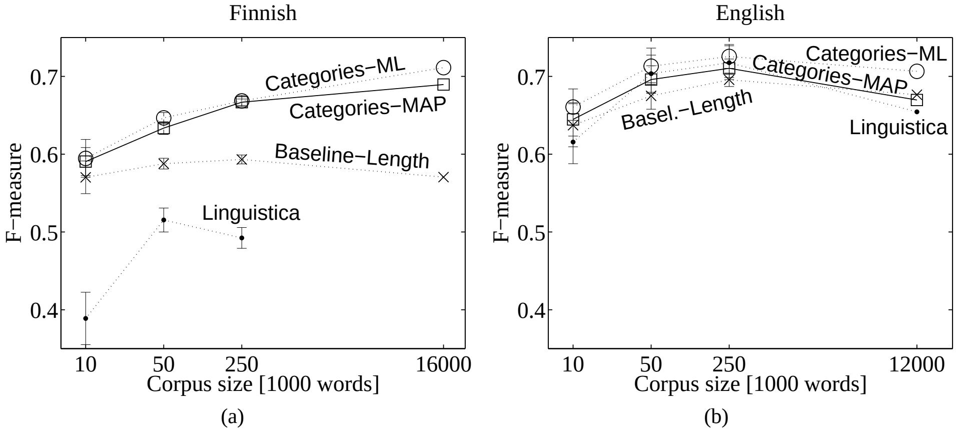
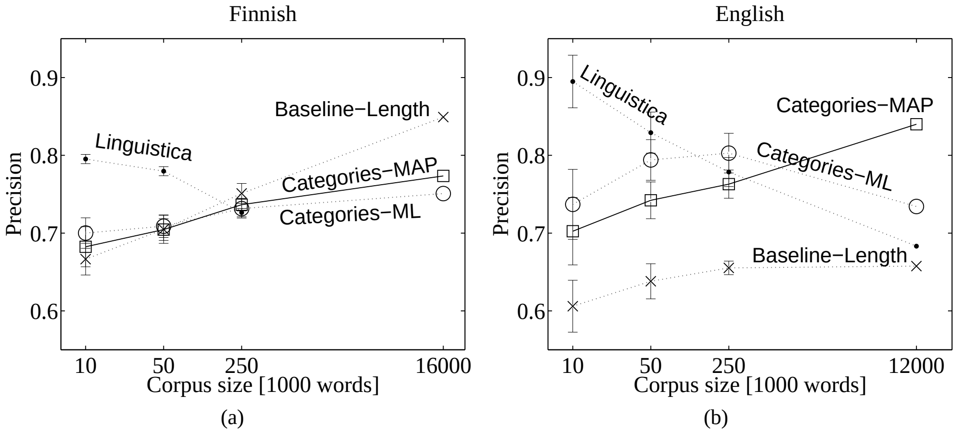


Fig. 6. Morpheme segmentation performance (F-measure of discovered morpheme boundaries) of the algorithms on (a) Finnish and (b) English test data. Each data point is an average of 5 runs on separate test sets, with the exception of the 16 million words for Finnish and the 12 million words for English (1 test set). In these cases the lack of test data constrained the number of runs. The standard deviations of the averages are shown as intervals around the data points. There is no data point for Linguistica on the largest Finnish test set, because the program is unsuited for very large amounts of data due to its considerable memory consumption.

5.5.1 *Baseline-Length.* When evaluated against a linguistic morpheme segmentation, the Baseline methods suffer because they undersegment frequent strings (e.g., English 'having, soldiers, states, seemed'), especially when trained on word token collections (where several word forms occur a high number of times). With more data, the undersegmentation problem becomes more severe also when trained on word type collections (where each unique word form is encountered only once). This is due to the fact that the addition of more examples of frequent word segments justify their inclusion as morphs of their own in the lexicon. This shows as a decrease in overall performance on the largest data sizes in Figure 6 and in recall in Figure 8.

The opposite problem consists in the oversegmentation of infrequent strings (e.g., 'flu+s+ter+ed'). Moreover, the method makes segmentation errors that ensue from considering the goodness of each morph without looking at its context in the word, causing errors such as in Table II 'ja+n+ille' where 'ja' is incorrectly identified as a morph because it is frequently used as a suffix in the Finnish language. These kinds of segmentation errors are particularly common with English, which explains the generally low precision of the method in Figure 7b.

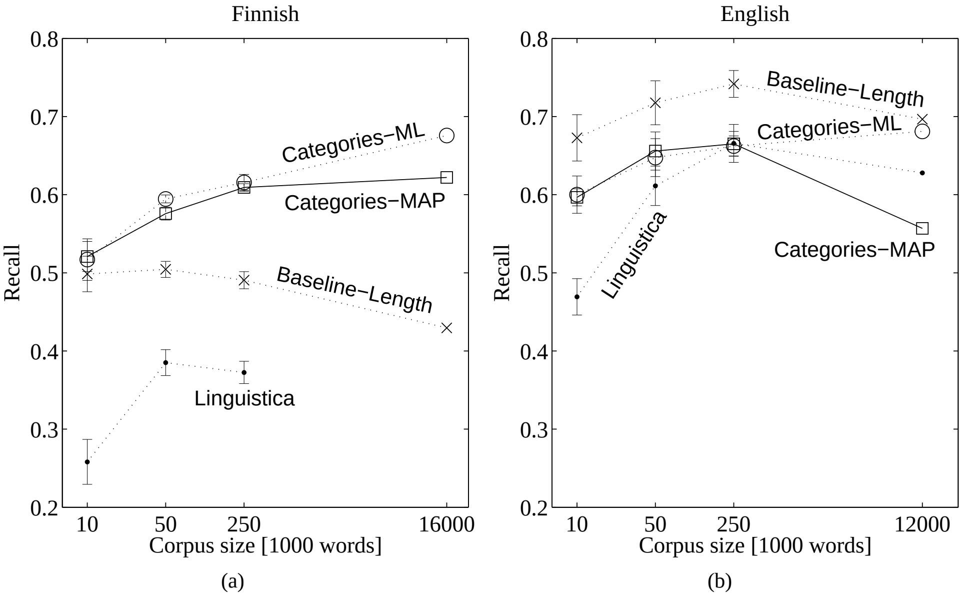
5.5.2 *Categories-ML.* Out of the compared methods Categories-ML shows the highest results in Figure 6 for both Finnish and English consistently with all data sizes. When compared to Baseline-Length in Figures 7a and 8a it appears that the considerable improvement is due to the fact that many previously undersegmented words have been split into smaller parts by Categories-ML: Many of the new proposed boundaries are correct (higher recall), but some are incorrect (lower precision). Apparently the simple morphotactics helps correct many mistakes caused by the lack of specific contextual information. However, the morphotactics is fairly primitive, and consequently new errors emerge when incorrect al-



(a)

(b)

Fig. 7. Precision of discovered morpheme boundaries obtained by the algorithms on (a) Finnish and (b) English data. Standard deviations are shown as intervals around the data points.



(a)

(b)

Fig. 8. Recall of discovered morpheme boundaries obtained by the algorithms on (a) Finnish and (b) English data. Standard deviations are shown as intervals around the data points. Whereas precision (Fig. 7) measures the accuracy of the proposed splitting points, recall describes the coverage of the splits.

ternations of stems and suffixes are proposed, e.g., Finnish: 'epä+este+et+t+isi+ksi' (plural translative of 'epäesteettinen', "unaesthetic"), 'työ+tapa+a+mine+n' ('työ+tapaa+minen', "job meeting"). The drop in precision for Categories-ML with the largest English data set (Fig. 7b) is apparently caused by the multitude of word forms (many foreign words and names), which give rise to the discovery of "suffixes" that are not considered correct in contemporary English, e.g., 'plex+us, styl+us'.

5.5.3 *Categories-MAP.* Figure 6a shows that Categories-MAP challenges Categories-ML as the best-performing algorithm for Finnish. For two data sizes (10 000 and 250 000 words) the difference between the two is not even statistically significant (T-test level 0.05). Also for English (Figure 6b), where the difference between all the algorithms is overall smaller than for Finnish, Categories-MAP places itself below the best-forming Categories-ML and above the Baseline-Length method, except on the largest data set, where it falls slightly below Baseline-Length. Note, however, that the difference in performance is statistically significant only between Categories-ML and the lowest-scoring algorithm at each data size (Linguistica at 10 000 words; Baseline-Length at 50 000 and 250 000 words).

When looking at the detailed measures in Figures 7 and 8 one can see that Categories-MAP performs very well for Finnish, with both precision and recall rising as new data is added. However, for English there is a fall-back in recall on the largest data set (Fig. 8b) , which is also reflected in decreased F-measure. This seems to be due to the fact that only the most frequent English prefixes and suffixes are detected reliably. In general, Categories-MAP is a more conservative splitter than Categories-ML.

5.5.4 *Linguistica.* Linguistica is a conservative word splitter for small amounts of data, which explains the low recall, but high precision for small data sets. As the amount of data increases, recall goes up, and precision goes down, because more and more signatures (paradigms) are suggested, some of them correct and some incorrect. At some point, the new signatures proposed are mainly incorrect, which means that both precision and recall decrease. This can be observed as peculiar suffixes of words, e.g., 'disappoi+nt, longitu+de, presentlyfou+nd, sorr+ow'. The recall of Linguistica can never rise very high, because the algorithm only separates prefixes and suffixes from the stem and thereby misses many boundaries in compound words: e.g, 'longfellow+'s, masterpiece+s, thanksgiv+ing'.

Linguistica cannot compete with the other algorithms on the Finnish data, but for English it works at the level of Categories-ML for the data sets containing 50 000 and 250 000 words. (Note that Linguistica was not run on larger data sets for Finnish than 250 000 words, because the program is unsuited for very large amounts of data due to its considerable memory consumption.)

5.5.5 *Behavior with different amounts of data.* In the experiments on Finnish, Categories-ML and Categories-MAP both improve their performance with the addition of more data. The rising curves may be due to the fact that these models have more parameters to be estimated than the other models, due to the HMM model for categories. The larger number of free parameters require more data in order to obtain good estimates. However, on the largest English set, all algorithms have difficulties, which seems to be due to the many foreign words contained in this set: Patterns are discovered that do not belong to contemporary English morphology.

Linguistica does not benefit from increasing amounts of data. The best results were obtained with medium-sized data sets, around 50 000 words for Finnish and 250 000 words for English. Similarly, Baseline-Length does not seem to benefit from ever-increasing data sizes, as it reaches its best performance with the data sets of 250 000 words.

5.6 Computational requirements

The Categories-MAP algorithm was implemented as a number of Perl scripts and makefiles. The largest Finnish data set took 34 hours and the largest English set $2\frac{1}{2}$ hours to run on an AMD Opteron 248, 2200 MHz processor. The memory consumption never exceeded 1 GB. The other algorithms were considerably faster (by an order of magnitude), but Linguistica was very memory-consuming.

6. DISCUSSION

Only the accuracy of the placement of morph boundaries has been evaluated quantitatively in the current paper. It is worth remembering that the gold standard splitting used in these evaluations is based on a traditional morphology. If the segmentations were evaluated using a real-world application, perhaps somewhat different segmentations would be most useful. For example, the tendency to keep common words together, seen in the Baseline and Categories-MAP models, might not be bad, e.g., in speech recognition or machine translation applications. In fact, quite the opposite, excessive splitting might be a problem in both applications.

The algorithms produce different amounts of information: the Baseline and Baseline-Length methods only produce a segmentation of the words, whereas the other algorithms (Categories-ML, Categories-MAP and Linguistica) also indicate whether a segment functions as a prefix, stem, or suffix. Additionally, by expanding the entries in the lexicon learned by Categories-MAP, a hierarchical representation is obtained, which can be visualized using a tree structure or nested brackets.

We will use the example segmentations obtained for a number of Finnish and English words (in Tables II and III) to briefly illustrate some aspects *beyond* the discovery of an accurate morpheme *segmentation* of words. In Table II, the gold standard segmentations for the Finnish words are given as a reference, whereas examples for Linguistica are lacking, because the algorithm could not be run on the largest Finnish test set. English results are available for Linguistica in Table III, but here the corresponding gold standard segmentations are not included, due to limited space and to the fact that all readers are familiar with the English language. Readers interested in the analyses of further word forms can try our demonstration program on the Internet[15].

6.1 Tagging of categories

As has been shown, the introduction of a simple morphotactics, or word-internal syntax, in the Categories models reduced the occurrences of under- and oversegmented words as well as misalignments due to the insensitivity of context, which were observed in the Baseline models. Examples of such cases in Tables II and III comprise the Finnish words ‘aarre+kammio+i+ssa’ (“in treasure chambers”), ‘jani+lle’ (“for Jani”), ‘sano+tta+ko+on’ (“may it be said”); and the English words ‘photo+graph+er+s’ and ‘fluster+ed’.

Additionally, the simple morphotactics can sometimes resolve semantic ambiguities, when the same morph is tagged differently in different contexts, e.g., ‘pää’ is a prefix in ‘pääaiheesta’ and ‘pääaiheista’ (“about [the] *main* topic(s)”), whereas ‘pää’ is a stem

[15] `http://www.cis.hut.fi/projects/morpho/`

Table II. Examples of Finnish morpheme segmentations learned by versions of Morfessor from the 16 million word Finnish test set. Additionally, the corresponding gold standard segmentations are supplied. Proposed prefixes are underlined, stems are rendered in **bold-face**, and suffixes are *slanted.* Square brackets [ ] indicate higher-level stems and parentheses () higher-level suffixes in the hierarchical lexicon.

Baseline-Length	Categories-ML	Categories-MAP	Gold standard
aarre kammioissa	**aarre kammio** *i ssa*	[**aarre kammio**] *issa*	**aarre kammio** *i ssa*
aarre kammioon	**aarre kammio** *on*	[**aarre kammio**] *on*	**aarre kammio** *on*
bahama laiset	**bahama lais** *et*	**bahama** *laiset*	**bahama** *laise t*
bahama saari en	**bahama saar** *i en*	**bahama** [**saari** *en*]	**bahama saar** *i en*
epä esteettis iksi	epä **este** *et t isi ksi*	epä [[**esteet** *ti*] *s*] *iksi*	**epäesteett** *is i ksi*
epätasapaino inen	epä tasa **paino** *in en*	[epä [[tasa **paino**] *inen*]]	epätasa **painoinen**
haapa koskeen	**haap** *a* **koske** *en*	[**haapa** [**koskee** *n*]]	**haapa koske** *en*
haapa koskella	**haap** *a* **koske** *lla*	[**haapa** [**koske** *lla*]]	**haapa koske** *lla*
ja n ille	**jani** *lle*	**jani** *lle*	**jani** *lle*
jäädyttä ä kseen	**jäädy** *ttä ä kseen*	[**jäädy ttää**] *kseen*	**jäädy** *ttä ä kse en*
ma clare n	**maclare** *n*	**maclare** *n*	–
nais autoilija a	nais **auto** *ili ja a*	[nais [**autoili** *ja*]] *a*	**nais autoili** *ja a*
pää aiheesta	pää **aihe** *e sta*	**pää** [**aihe** *esta*]	**pää aihee** *sta*
pää aiheista	pää **aihe** *i sta*	[pää [**aihe** *ista*]]	**pää aihe** *i sta*
päähän	**pää** *hän*	[pää **hän**]	**pää** *hän*
sano t takoon	**sano** *tta ko on*	[**sano ttakoon**]	**sano** *tta ko on*
sano ttiin ko	**sano** *tti in ko*	[**sano** *ttiin*] *ko*	**sano** *tt i in ko*
työ tapaaminen	työ **tapa** *a* **mine** *n*	**työ** [**tapaa** *minen*]	**työ tapaa** *minen*
töhri misistä	**töhri** *mis i stä*	**töhri** (*mis istä*)	**töhri** *mis i stä*
voi mmeko	**voim meko**	[[**voi** *mme*] *ko*]	**voi** *mme ko*
voisi mme kin	**voisi** *mme kin*	[**voisi** *mme*] *kin*	**vo** *isi mme kin*

Table III. Examples of English morpheme segmentations learned by the four algorithms from the 12 million word English test set.

Baseline-Length	Categories-ML	Categories-MAP	Linguistica
accomplish es	**accomplish** *es*	[**accomplish** *es*]	ac **compli** *shes*
accomplish ment	**accomplish** *ment*	[**accomplish ment**]	**accomplish** *ment*
beautiful ly	**beauti** *ful ly*	[**beautiful** *ly*]	**beautiful** *ly*
configu ration	con **figu** *r ation*	[**configur ation**]	con **figura** *tion*
dis appoint	dis **appoint**	**disappoint**	**disappoi** *nt*
expression istic	**express** *ion ist ic*	**expression istic**	**expression** *istic*
express ive ness	**express** *ive ness*	[**expressive** *ness*]	**expressive** *ness*
flu s ter ed	**fluster** *ed*	[**fluster** *ed*]	**fluster** *ed*
insur e	**insur** *e*	**insure**	**insur** *e*
insur ed	**insur** *ed*	[**insur** *ed*]	**insur** *ed*
insur es	**insur** *es*	[**insure** *s*]	**insure** *s*
insur ing	**insur** *ing*	[**insur** *ing*]	**insur** *ing*
long fellow ’s	**long fellow** *’s*	[[**long fellow**] *’s*]	**longfellow** *’s*
master piece s	**master piece** *s*	[[**master piece**] *s*]	**masterpiece** *s*
micro organism s	**micro organ** *ism s*	[**micro** [**organism** *s*]]	micro **organism** *s*
photograph ers	**photo graph** *ers*	[[[**photo graph**] *er*] *s*]	**photograph** *ers*
present ly found	**present lyfound**	[**present** *ly*] **found**	**presentlyfou** *nd*
re side d	re **side** *d*	**resided**	**resid** *ed*
re side s	re **side** *s*	[**reside** *s*]	**reside** *s*
re s id ing	re **sid** *ing*	[re **siding**]	**resid** *ing*
un expect ed ly	un **expect** *ed ly*	[[un [**expect** *ed*]] *ly*]	un **expected** *ly*

in ‘päähän’ (“in [the] *head*”). (In this example the Categories-ML algorithm tagged the occurrences of ‘pää’ correctly, whereas Categories-MAP made some mistakes.)

From the point of view of natural language processing, the identification and separation of semantic segments (mainly stems) and syntactic segments (mainly affixes) can be beneficial. The stems contained in a word form could be considered as a canonic (or base) form of the word, whereas the affixes could be considered as inflections. Such a canonic form for words could be an alternative to the base forms retrieved by hand-made morphological analyzers or stemming algorithms, which are used, e.g., in information retrieval.

6.2 Bracketing

The hierarchical representation produced by the Categories-MAP algorithm, shown using nested brackets in Tables II and III, can be interpreted as the attachment hierarchy of the morphemes. With the current model, the construction of the hierarchy is likely to take place in the order of most frequently co-occurring word segments. Sometimes this is also grammatically elegant, e.g., Finnish: ‘[epä [[tasa paino] inen]]’ (“imbalanced”, literaly bracketed as “[un [[even weight] ed]]”), ‘[nais [autoili ja]] a’ (partitive of “[female [car-driv er]]”; English: ‘[[[photo graph] er] s], [[un [expect ed]] ly]’. But the probability of coming up with grammatically less elegant solutions is also high, e.g., English ‘[micro [organism s]]’. (Note that the gold standard segmentation for ‘epätasapainoinen’ is strange. Categories-MAP produces the correct segmentation.)

6.3 Overgeneralization

The algorithms can incorrectly “overgeneralize” and, for instance, suggest a suffix, where there is none, e.g., ‘maclare+n’ (“MacLaren”). Furthermore, nonsensical sequences of suffixes (which in other contexts are true suffixes) can be suggested, e.g., ‘epä+este+et+t+isi+ksi’, which should be ‘epä+esteett+is+i+ksi’. A model with more fine-grained categories might reduce such shortcomings in that it could model morphotactics more accurately.

The use of signatures in Linguistica should conceivably prevent overgeneralization. In general, to propose the segmentation ‘maclare+n’, other forms of the proposed stem would be expected to occur in the data, such as ‘maclare’ or ‘maclare+ssa’. If none of these exist, the segmentation should be discarded. However, especially with large amounts of data Linguistica is oversensitive to common strings that occur at the end of words and proposes segmentations, such as ‘allu+de, alongsi+de, longitu+de’; ‘anyh+ow, highbr+ow, longfell+ow’.

Solutions to this problem could be found, e.g., in the approach advocated by Yarowsky and Wicentowski [2000], who study how distributional patterns in a corpus can be utilized to decide whether words are related or not. For instance, their method is able to determine that the English word ‘singed’ is not an inflected form of ‘to sing’.

6.4 Allomorphy

Allomorphs are morphs representing the same morpheme, i.e., morphs having the same meaning but used in complementary distributions. The current algorithms cannot in principle discover which morphs are allomorphs, e.g., that in Finnish ‘on’ and ‘en’ mark the same case, namely illative, in ‘aarre+kammio+on’ (“into [the] treasure chamber”) and

'Haapa+koske+en' ("to Haapakoski").[16] To enable such discovery in principle, one would probably need to look at contexts of nearby words, not just the word-internal context. Additionally, one should allow the learning of a model with richer category structure.

Moreover, 'on' and 'en' do not always mark the illative case. In 'bahama+saari+ en' ("of the Bahama islands") the genitive is marked as 'en', and in 'sano+tta+ko+on' ("may it be said") 'on' marks the third person singular. Similar examples can be found for English, e.g., 'ed' and 'd' are allomorphs in 'insur+ed' vs. 're+side+d', and so are 'es' and 's' in 'insur+es' vs. 're+side+s' (Categories-ML).

Many cases of allomorphy can be modeled using morpho-phonological rules. The so called Item and Process (IP) model of morphology assumes that some canonic forms of morphemes are appended to each other to form words, and when the morphemes meet, sound changes may ensue typically at the morpheme boundaries. For instance, the final 'e' in 'insure' is dropped when followed by the suffix 'ed'. In principle, such rules could be learned in an unsupervised manner from unannotated data. Kontorovich et al. [2003] apply machine learning in the acquisition of allomorphic rules, but their method requires aligned training data.

Quite generally, much of the work in unsupervised morphology learning does not focus on concatenative morphology, i.e., the discovery of consecutive word segments. Some algorithms learn relationships between words by comparing the orthographic and semantic similarity of pairs of words, e.g., [Neuvel and Fulop 2002; Baroni et al. 2002]. These approaches can handle non-concatenative morphological processes, such as the Unmlaut sound change in German. However, none of these models as such suits highly-inflecting languages as they assume only two or three constituents per word, analogous to possible prefix, stem and suffix.

Moreover, there is some evidence that humans may simply memorize allomorphs as such without applying morpho-phonological transformations on what they hear (or read) [Järvikivi and Niemi 2002]. In this case, the morphology-learning models presented in this work are perhaps closer to human language processing than the IP model of morphology.

7. CONCLUSION

We have attempted to provide the reader with a broad understanding of the morphology learning problem. It is hoped that the presented general probabilistic model family, called Morfessor, and the discussion of each component opens new and fruitful ways to think about modeling morphology learning. The experimental comparison of different instances of the general model in a morpheme segmentation task sheds light on the usefulness and role of particular model components.

The development of good model search algorithms deserves additional consideration in the future. The categorial labelings of the morphs produced by the later model variants might be useful in other tasks, such as information retrieval. An interesting avenue for future research is the consideration of how to extend the feature set applied in the modeling of morph usage, possibly to the point where one is able to ground meanings of morphs using multimodal information.

[16] Furthermore the algorithm cannot deduce that the illative is actually realized as a vowel lengthening + 'n': 'kammioon' vs. 'koskeen'.

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