Handling Compounding in Mobile Keyboard Input

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Abstract

This paper proposes a framework to improve the typing experience of mobile users in morphologically rich languages. Smartphone keyboards typically support features such as input decoding, corrections and predictions that all rely on language models. For latency reasons, these operations happen on device, so the models are of limited size and cannot easily cover all the words needed by users for their daily tasks, especially in morphologically rich languages. In particular, the compounding nature of Germanic languages makes their vocabulary virtually infinite. Similarly, heavily inflecting and agglutinative languages (e.g. Slavic, Turkic or Finno-Ugric languages) tend to have much larger vocabularies than morphologically simpler languages, such as English or Mandarin.

We propose to model such languages with automatically selected subword units annotated with what we call “binding types”, allowing the decoder to know when to bind subword units into words. We show that this method brings around 20% word error rate reduction in a variety of compounding languages. This is more than twice the improvement we previously obtained with a more basic approach, also described in the paper.

With fast-growing use of mobile devices, offering an efficient and pleasant mobile text input experience has recently become a topic of great interest to researchers and technology providers. Speech recognition, for example, has flourished in the last few years, mostly fueled by the need for convenient mobile input methods (Schalkwyk et al., 2010). Likewise, handwriting recognition has gained more traction, especially in languages with complex scripts such as Chinese and Indic languages (Keysers et al., 2016).

Relatively speaking, keyboard input has received less attention from the research community, even though it remains a primary input method as it is generally considered, whether rightfully so or not, to be the most straightforward way to input text on a mobile device. As we will see in this paper, the typing experience of users with morphologically rich languages may be quite suboptimal if no special care is taken to model linguistic phenomena such as compounding explicitly.

The main function of a soft keyboard is to decode users’ touch inputs into words and sentences, just like a speech recognizer would decode input waveforms. Advanced keyboards support “tap typing”, where users tap the keys corresponding to the characters of a word, and “gesture typing”, where they swipe their finger across the layout of the keyboard. The keyboard decoder typically also offers “autocorrections”, “word suggestions” (or “word completions”), and “next word predictions”, all of which aim at assisting the user in recovering from typos and “fat finger” errors, and ultimately at reducing the number of keystrokes required to compose a given text.

Keyboard input decoding is generally performed on device, which imposes strict constraints on model sizes. Typically an embedded language model is limited to one to ten megabytes on today’s mainstream devices.

In this context, correctly handling morphological variants is complicated. Human languages display a wide variety of morphological phenomena which linguists have described and categorized, all resulting in fast growth of the language’s vocabu-
lary size. Model vocabularies are normally determined by making the simplistic, but usually extremely effective, assumption that text can simply be split into useful units by using whitespace as a separator. Big word vocabularies are a problem for the paradigm of small language models, especially when these models are also expected to provide enough contextual depth to support features such as next-word prediction.

We propose a framework to handle certain classes of morphological phenomena, such as compounding, agglutination and contraction. We model distinct subword units (stems and affixes or constituents of compounds), and we impose programmatic constraints on how these can combine. The framework rests on a finite-state transducer (FST) representation of the underlying decoding models, similar to the familiar speech recognition FST decoding theory.

The rest of this paper contains more background on keyboard input (Section 1), how keyboard improvements can be measured (Section 2), an introduction to morphology (Section 3), how it affects keyboard input and a simple solution to mitigate the issue (Section 4), and a more generic solution, with application and results for some compounding languages (Section 5).

1 Keyboard Input

1.1 Keyboard Decoding

A tapped input consists of a time series of touch points, \( x \), that encodes the coordinates of the user’s key presses. For gesture input, the input trajectory is sampled, e.g. every 100 milliseconds, to provide a similar time series. The task of the decoder is to find the word sequence \( w^* \) that best matches the input sequence \( x \).

The decoder relies on a spatial model to provide a probability distribution over a set of spatial units for a given touch point, and a language model to enforce word spellings and respect word sequence probabilities. The spatial model for tap input is typically a Gaussian distribution centered on each key center. Gesture inputs instead are often modeled with the so-called “minimum-jerk model” that imposes smoothness maximization constraints on the input trajectory (Quinn and Shumin, 2016). Alternatively, a recurrent neural network model can be used (Alsharif et al., 2015).

Given a spatial model and a language model, the keyboard decoder finds the most likely word sequence given the input, \( w^* = \text{argmax}_w P(w|x) \), or \( w^* = \text{argmax}_w P(x|w)P(w) \) with Bayes rule, which is reminiscent of the fundamental equation of speech recognition. Accordingly, one can easily adopt a finite-state transducer (FST) representation as in automatic speech recognition (Mohri et al., 2008). The details of such an implementation are not critical to this paper, and one example may be found in (Ouyang et al., 2017).

1.2 Keyboard Language Models

Similar to the language models that power embedded speech recognition systems, keyboard language models are typically n-grams of relatively low order over a limited vocabulary (McGraw et al., 2016). Typical order of magnitudes may be 3-grams with 64K to 128K words, and a couple of million n-grams.

Because of keyboard features like suggestions, completions and predictions where the language model is more prominent than the spatial model, the language model should be carefully crafted. For example, if a user gestures “refereed”, they may expect the keyboard to suggest “referred” as an alternative, but not misspellings such as “reffered” or “reffered” which may appear with non-negligible frequency in the training corpus, as most corpora contain typos. These four words have the same spatial score, since the gestures to produce them are identical; if their language model scores are close enough, one of the typos may be presented as a suggestion for the original input. Keyboard users typically find this annoying, as they often view the keyboard as a lexical reference as well as an input method.

For this reason, keyboard language models are typically trained to a fixed vocabulary that has been hand-curated to eliminate misspellings, erroneous capitalizations, and other undesired artifacts.

2 Keyboard Testing

The rigorous testing of a keyboard decoder and its models is complex. For one thing, keyboard input methods are interactive; users can tap, select suggestions, backspace, tap again, and so on. In contrast, speech inputs are continuous, short of occasional hesitations and dysfluencies. Moreover, it is not easy to “transcribe” a sequence of touch
points the way one transcribes a speech waveform or a handwritten sentence: our brains are not used to performing this task.

For these reasons, the quality of a keyboard is typically assessed through simulations. Sentences representative of the expected user inputs are collected in a test set. For each sentence, $w$, an input sequence $x$ is simulated using the keyboard spatial model as a generative engine. The sequence is then decoded, and the resulting word string $w^*$ is compared to the original string, $w$. A “word error rate” (WER) can be computed over all sentences in the test set.

Additional metrics can be tracked to evaluate other facets of the system, e.g. “keystroke saving” for word completion efficiency, next word prediction accuracy, but we will focus on the WER, which illustrates well language model quality improvements.

3 Morphology

3.1 Background

Morphology concerns the analysis of words into their smallest meaningful units. These units are abstract (and may not even be contiguous, as in circumfixing and “nonconcatenative” languages, but this is beyond the scope of this work). Here, we are interested primarily in addressing three phenomena.

The first is inflection, where a single word changes forms due to syntactic usage; for example, in English, verbs inflect with endings like “-ing” and “-s” (“eat,” “eating,” “eats”). This phenomenon is more prevalent in languages with complex verb conjugations (e.g. Romance language verb paradigms), languages with freer word order, where nominal expressions are inflected for case in addition to number and gender (e.g. the Slavic languages), and even more so in so-called agglutinative languages like Turkish.

The second phenomenon is contraction, where words, syllables or groups of words are shortened by omitting internal letters. For example, French makes use of elisions to contract pronouns and prepositions with verbs (“j’aime”, “je l’aime”, “je n’aime pas”).

The third phenomenon is compounding, where two or more words combine to form a new lexical item; this phenomenon tends to be restricted in English (e.g. “lifeboat”) but is highly productive in many languages, like Dutch, Danish, and German.

By modeling subword units (e.g. stems/affixes or compound constituents) rather than full words, we can reduce the size of the language models while keeping their expressivity constant or even allowing their coverage to grow.

3.2 Compounding Languages

While our approach is very general, we focus mostly on compounding in this paper. In English it is possible for multiple free morphemes to bind together, as in “flashlight,” where both “flash” and “light” are individually meaningful and valid words. Two-word compounds are a common word-formation strategy in many languages; in languages such as Sanskrit and many Germanic languages, multiple-unit compounding is a productive phenomenon.

German words undergo additional changes when compounding occurs. Because of this, we cannot simply model compounds as the junction of two words. For example, the words “Schwan” (“swan”) and “gesang” (“song”) combine to form “Schwanengesang,” where “-en-” is an interfix (the so-called “glue morpheme”). Likewise the “-s-” in “Ordnungssinn” (“sense of order”), where the lexical components are “Ordnung” and “Sinn.” Alternatively, a final weak vowel may disappear in compounding, as in “Schulbus” (“schoolbus”), where the first morpheme usually shows up as “Schule” (“school”). In all of these cases, because the first morpheme undergoes alteration in compounding, the surface form would be out-of-vocabulary from the model’s perspective (i.e., “Schwan” shows up but not “Schwanen,” “Schule” but not “Schul,” etc.).

3.3 Modeling Morphology

There have been numerous efforts to improve speech recognition through morphological and subword language models. This includes early attempts to incorporate morphological analysis into semantic language models (Elbeze and Derouault, 1990) as well as work that explicitly incorporates morphological components into the language model for decoding (Sak et al., 2010; El-Desoky et al., 2010). These models typically are of two varieties; improved word modeling by allowing for richer analysis of words, and subword modeling where word-forms are split based on a morphologically-inspired analysis (e.g., stemming
where inflectional affixes are split form the stem of the word form). To our best knowledge, there is no literature on morphology handling for keyboard input, where as we will see the issue materializes slightly differently.

4 Compounding and Keyboard Input

The lack of consistent support for compounding makes many ad-hoc compounds out-of-vocabulary (OOV) in our lexicon and language model (LM). Typing an OOV compound in a soft keyboard may result in one of several undesired behaviors. In the best case, if the user taps the word carefully, the word will be decoded “literally” (meaning letter-by-letter), but will be red-underlined as it is unknown to the system. Alternatively, if the components of the compound are in-vocabulary, the word may be split in its components by the decoder. Worse, if one of the constituents of the compound is OOV, it will be auto-corrected to another word.

The simple word splitting behavior is frequent enough and simple enough to prevent that we started with a heuristic for this specific case.

4.1 Heuristic to Handle Simple Compounds

Simple compound splitting happens when the insertion of a word separator is the cheapest spatial change that makes the input in-vocabulary. It will almost always be unacceptable to the user, as word splitting changes the meaning of the phrase, or even renders it ungrammatical. To reduce the number of unwanted word splits, we implemented a postprocessing step in our decoder logic that would try to identify word splits introduced by the decoder where the user likely intended a compound (as opposed to missing a white space).

Experimentation converged on the following, highly heuristic prescription:

- iterate through decoder candidates for the current word (i.e., user input between user-entered word separators) in order of descending spatial model score
- if a two-word candidate is found, insert an additional decoder result for the concatenation of the two words and with a slightly improved spatial score, and return
- if a three-... word candidate is found, return with the result list unchanged.

The rationale behind these prescriptions is that the LM score for the two-word candidate is unrelated to the likelihood of the compound, and that the likelihood of over-generating or ‘rambling’ will increase if we consider spatially less likely candidates.

For German, we would only consider candidates in which both words were capitalized (indicating that both are common nouns). When encountering a two-word candidate with one or both words lower-cased, we would still consider spatially lower-scoring two-word candidates, but only if all higher-scoring candidates were case variants. The generated candidate would be the concatenation of the first word and the lower-cased second word. This confined us to the unambiguous case of nouns composed of other nouns, while still allowing us to find such candidates in the frequent case of nouns and verbs only differing in case.

For all other languages, we would only consider candidates for which both words were lower-case, and would not consider candidates of lower spatial score than the first two-word candidate.

The score boost for undoing a word split has to be tuned experimentally to find a good compromise between coverage and precision. Results with this method are summarized in Table 1.

5 Binding Types

The simple approach described above is highly heuristic. In this section, we propose a more principled approach that leverages the flexibility of the FST decoder.

5.1 Subword Unit Modeling with Binding Types

Compounding languages can generate infinitely many distinct words; traditional word-based n-gram models, however, are designed to handle similarly unlimited set of word sequences: An English word-based n-gram model will be able to deal with *summer day* when it knows about *winter day* and *summer*, yet a strictly word-based German model would explicitly have to know the analogous formation *Sommertag*.

Hence, a natural approach is to map compounds to n-grams, thus promoting subword units to words, known compounds to known n-grams, and, crucially, unknown compounds to backed-off n-grams. At training time, we automatically determine the inventory of subword units using a de-
Table 1: Comparison of word error rates between a baseline decoder and one with post-decoding compound rewriting step. Each test set contains around 20,000 sentences.

| Language | WER | WER$_{rw}$ | ΔWER |
|----------|-----|-------------|------|
| Danish   | 17.1% | 16.4% | -3.9% |
| Dutch    | 17.3% | 16.4% | -5.0% |
| Finnish  | 18.2% | 15.9% | -12.4% |
| German   | 11.3% | 11.1% | -1.6% |
| Norwegian | 17.9% | 16.9% | -5.6% |
| Swedish  | 19.6% | 18.14% | -7.5% |

It is important that we still distinguish between sequences forming compounds and sequences of individual words: First, compound parts may not even be words in their own right, due to interfixes or elisions. Second, sequences such as Sommer Tag can be grammatical, and will in general differ in frequency from the compound Sommertag.

In our approach, a subword unit is uniquely specified by its text and by its 'binding type', comprising two non-negative integers—its left and right 'binding class', here notated with left subscript and right superscript. We require that right and left binding classes of two consecutive subword units agree. A left (right) binding class of 0 marks a left (right) proper word boundary, all other binding classes denote composition.

Thus, for an English subword lexicon comprising

$$\{0\text{foot}^1, 0\text{base}^1, 1\text{ball}^0, 0\text{foot}^0, 0\text{base}^0, 0\text{ball}^0\},$$

the rules would allow $0\text{base}^0\text{ball}^0$ and $0\text{foot}^0\text{ball}^0$, and forbid all variants of $0\text{base}^0\text{base}^m$ but $k = m = 0$ (i.e., the two-word sequence base base.)

With one inner binding class, a token can be classified as $0\text{word}^0, 0\text{prefix}^1, 1\text{infix}^1, 1\text{suffix}^0$. Adding binding classes $> 1$ allows for more fine-grained control, or even for the addition of different morphological phenomena. For example, adding

$$\{0\text{un}^2, 2\text{usual}^0, 2\text{happy}^0\}$$

to the above would capture adjective negation, while avoiding $0\text{un}^2\text{ball}^0$.

For a given set of such subword units with binding classes $0..N$, a lexicon FST (i.e., a FST mapping keys to sequences of subword ids) can be constructed the following way: Let $L_s$ be a subword unit key-to-word-id FST and $R^l,r_{(N)}$ an acceptor for subword units of binding type $(l, r)$. By iterating

$$R^l,r_{(n-1)} = R^l,n + R^l,n(R^n,n)^*R^l,r,$$

(using $+$ for union and an obvious notation for concatenation and Kleene star) one obtains an acceptor for all single-word subword sequences: $W = R^l,0$, and the word-level lexicon FST is the composition $L_w = (L_sL_s^*) \circ W$.

By construction, the subword id sequences generated by this lexicon FST will be well-formed: traversing the FST once will result in a complete, rule-conforming sequence spanning exactly one proper word. Furthermore, it will generate all such sequences that are compatible with its input; whether one of these sequences has been seen in training will be reflected in their LM score. Note that, in general, $L_w$ will be non-functional, reflecting the fact that compound analysis need not be unique, as in German Staubecken, which may be analyzed as Stau + Becken (dam reservoir) or Staub + Ecken (dusty corners).

For all languages we investigated, the resulting lexicon was somewhat smaller (by a few percent) than a lexicon for a purely word-based model, all other training parameters kept unchanged.

Note that we are not restricted to the simple ruleset above; it was chosen because it is easy to enforce at training and decoding time and kept changes to our training pipeline minimal, while being flexible enough to capture a variety of word formation mechanisms (simple prefixes/suffixes as well as potentially infinite sequences as in compounding). In principle, however, we could construct a lexicon using any regular language over subword classes.

Our scheme is easily implemented in LM training, as compound analysis is a preprocessing step in our pipeline; the compound parts are annotated in-text with unique affixes representing their binding type. The subsequent steps of the pipeline will consider them distinct words, and can remain unchanged. The token affixes can be stripped when the actual textual value is needed (lexicon building, decoder user interface).

The resulting LM, however, cannot be used as is. Suppose the LM FST scores the last token in a sequence ending in a compound bigram $0\alpha^1 1\beta^0$, and that bigram has not been seen in training (or has been pruned from the LM). The LM will successively back off to shorter context states, eventually from $0\alpha^1$ to the empty context $[]$. This state...
will have outgoing arcs for all pseudo-unigrams, words and subwords alike, with weights given by their background probabilities.

This vastly underestimates the actual likelihood of \( t b^0 \) occurring after \( 0 a^1 \): at both training and decoding time, its occurrence is conditioned on being preceded by a token of right binding class 1, while the unmodified LM will give the unconditional probability.

The remedy is to normalize the probabilities on arcs leaving the empty context state separately for each left binding class (which is equivalent to introducing per-binding class back-off states, \([0]^1\), \([1]^1\), ...). This renders the LM probabilistically correct: the probability sum over all admissible paths through the LM now is 1.

Realizing this was a crucial step: without this probabilistic correction, our German model suppressed compound back-off by \( e^{3.8} \), effectively restricting it to decoding/predicting compounds seen at training time.

5.2 Experiments

We ran experiments in Danish, Dutch, and German. We first trained baseline word-based language models using large corpora of anonymized messages and web documents. We then trained subword models from the same data, using in a preprocessing step the compound splitting library described in (Macherey et al., 2011), which was modified to further split compound parts into base word and interfix. The clean-up step of our pipeline, which marks out-of-vocabulary words by comparing against curated vocabularies, was modified to reject a split-compound n-gram only if the compound itself and all its constituents (base words, no interfix) were OOV. In that case, the compound was replaced with a single OOV token. Otherwise, interfixes were re-attached to their prefix, and the compound parts were annotated as described above, using a single inner binding class.

All pruning parameters were left unchanged between the baseline and the experimental configuration: 150k unigrams and 1.5M n-grams, with maximal n-gram order 3. The lexicon and LM FSTs were generated as described above. Table 2 gives word error rates with both approaches.

A more in-depth analysis of decoding results highlighted two mechanisms contributing to the WER reduction over our previous, heuristic solution:

| Language | WERsw | WERsw \( \Delta \) | \( \Delta \)WER | \( \Delta \)Ins |
|----------|-------|----------------|-------------|-------------|
| Danish   | 17.8% | 14.2%          | -20.2%      | -69.7%      |
| Dutch    | 16.7% | 13.9%          | -16.1%      | -75.0%      |
| German   | 10.6% | 8.5%           | -19.8%      | -71.4%      |

Table 2: Comparison of word error rates between word-based and subword-based language models. The relative change in insertion rate is a measure of reduction in erroneously split compounds.

(1) compounds with interfixes: German Versicherung (‘insurance’) becomes the non-word Versicherungs- when used as a compound prefix, making such compounds inaccessible for our heuristic trick of undoing the insertion of a word separator. It shares this property with all other verb nominalizations formed as stem + -ung. All such compounds had to be contained as words in our (purely enumerative) lexicon. Thus, we were able to decode Versicherungsvertreter (‘insurance salesman’), but not Versicherungsvertreterin (‘insurance saleswoman’); Versicherungsbetrug (‘insurance fraud’), but not Versicherungsbetrüger (‘insurance fraudster’).

(2) multi-word compounds: An actual example from our test sets is German Modell dampfmaschinenhändler, (‘model steam engine dealer’). The word-separation heuristic fails, as there are no two-word analyses of this ad-hoc formation: the individual words as well as the compound ‘steam engine’ are in the lexicon, but the three-word compounds ‘model steam engine’ or ‘steam engine dealer’ are not—if they occurred in the corpus at all, they are too infrequent. The remaining two-compound analysis Modell dampf + Maschinenhändler would require a nonsensical lexicon entry for ‘model steam’.

Our subword-based lexicon, however, maps the compound to the four-part sequence \((0)\text{Modell} (1)\text{Dampf} (1)\text{Maschinen} (1)\text{Händler}\). When scoring this, the LM backs off to the unigram level, except for \((1)\text{Maschinen} (1)\text{Händler}\). In a nice example of the generalization capabilities of a subword-based LM, the presence of that bigram can be traced back to Landmaschinenhändler (‘farm machinery dealer’) in our corpus, and of \(1\text{Dampf}\), to Quecksilverdampflampe (‘mercury-vapor lamp’).

6 Conclusion

We proposed a generic solution to handle a variety of morphological phenomena as they materi-
alize and affect users in soft keyboard input. We applied this approach to the case of compounding languages, and showed that it can drastically reduce the undesired splitting of compound words, and improve WERs by roughly 20% across languages. In future work, we will generalize our de-compounding models to more languages and phenomena and hence extend the reach of the proposed method.

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