Morpho-syntactic post-processing of *N*-best lists for improved French automatic speech recognition ☆

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Abstract

Many automatic speech recognition (ASR) systems rely on the sole pronunciation dictionaries and language models to take into account information about language. Implicitly, morphology and syntax are to a certain extent embedded in the language models but the richness of such linguistic knowledge is not exploited. This paper studies the use of morpho-syntactic (MS) information in a post-processing stage of an ASR system, by reordering *N*-best lists. Each sentence hypothesis is first part-of-speech tagged. A morpho-syntactic score is computed over the tag sequence with a long-span language model and combined to the acoustic and word-level language model scores. This new sentence-level score is finally used to rescore *N*-best lists by reranking or consensus. Experiments on a French broadcast news task show that morpho-syntactic knowledge improves the word error rate and confidence measures. In particular, it was observed that the errors corrected are not only agreement errors and errors on short grammatical words but also other errors on lexical words where the hypothesized lemma was modified.

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Keywords: Speech recognition; Morpho-syntax; Tagging; Confidence measure

1. Introduction

Word-based language models (LMs) are used in all current automatic speech recognition (ASR) systems. This kind of models is a convenient way to introduce knowledge about the language thanks to statistical methods based on the frequency of occurrence of sequences of words. However, these LMs only indirectly take into account high-level linguistic information about the language, while more explicit linguistic knowledge could be included, in particular morphology and syntax. The joint use of these two knowledge sources to improve transcription is the focus of this paper.

31   As a preliminary study to motivate this work, we analyzed the transcription errors on a 30 min excerpt of
32 French broadcast news in order to quantize the potential gain using knowledge about syntax or morphology.
33 The excerpt was transcribed using a 4-gram language model and exhibits a word error rate (WER) of 17.8%.
34 The first observation that can be made is that several parts of the transcript were not syntactically correct, errors
35 on short grammatical words being particularly frequent as they concern more than one out of five sentences.[2]
36 The most problematic words were the auxiliary verb forms "*a*", "*ont*" and "*est*", the prepositions "*dans*", "*en*",
37 "*de*" and " *á*", the conjunctions "*et*", "*ou*" and "*que*" and the determiners "*les*", "*des*", "*ces*" and "*ses*". Sec-
38 ondly, agreement errors account for 11.7% of the errors, where the recognition hypothesis is an homophone
39 of the actual word, e.g. a confusion between "*estivale*" and "*estivales*". However, some of these errors are very
40 difficult to correct, particularly those that require to resolve anaphora or to establish dependencies between dis-
41 tant words. The percentage of errors related to agreement is still 6.1% when solely counting gender and number
42 agreement errors that can be corrected by considering within sentence relations, which corresponds to 1.1 point
43 in the WER. This analysis of the errors clearly emphasizes that morphology and syntax are valuable knowledge
44 sources to correct typical errors of an ASR system and that the two are highly intricated.

45   In this work, we propose a new method to jointly include knowledge on morphology and syntax in order to
46 improve the word error rate. Previous studies have already considered morphology. For instance, the use of
47 sub-words (Kurimo et al., 2006) or of a set of features (Vergyri et al., 2004), instead of words as basic units for
48 ASR, leads to a reduction of the WER for agglutinative languages, with a dramatic reduction of out-of-vocab-
49 ulary words. However, the increased number of units in a segment prevents these methods from using LMs
50 with a long span history. Information about syntax was also previously added to the ASR process through
51 the use of a syntactic analyzer to condition probabilities of LMs (Chelba and Jelinek, 2000). Nevertheless,
52 the conception of robust syntactic parsers for oral documents still remains a difficult issue. Maltese and Man-
53 cini (1992) consider both morphology and syntax relying on two language models, one on lemmas and one on
54 parts-of-speech (POS). Interpolating word-level language models with class-based language models on mor-
55 pho-syntactic classes (Maltese et al., 2001) is another example of the joint use of both linguistic resources.

56   We propose a new approach to include morpho-syntactic (MS) information in a post-processing stage of
57 speech decoding, by reordering *N*-best lists. Our method relies on parts-of-speech, which in our case are gram-
58 matical classes (e.g. verb, noun, preposition, etc.) along with morphological information.[3] The idea is first to
59 automatically tag *N*-best lists, which allows the disambiguation of each hypothesized word according to its
60 MS class. Although the resulting information is more basic than the one induced by syntactic parsers, it
61 can be reliably inferred by automatic taggers, even on spoken documents with transcription errors, as shown
62 experimentally in this article. A morpho-syntactic score is then computed at the sentence level and combined
63 with the acoustic and language model scores. The combination of scores rather than models, along with the
64 limited number of tags, makes it possible to take into account long distance dependencies with a 7-gram class-
65 based LM. Finally, the new score including morpho-syntax is used to reorder *N*-best lists according to several
66 usual decoding criteria, or to compute confidence measures based on posterior probabilities.

67   This paper is organized as follows: Previous works on the use of morphology or syntax in ASR are pre-
68 sented in Section 2, with an emphasis on the French language. In Section 3, the ability of automatic taggers
69 to deal with spoken language and misrecognized words is demonstrated. Section 4 presents our contribution to
70 use MS information to rerank *N*-best lists. The experimental setup along with implementation details are pro-
71 vided in Section 5 while results on a French broadcast news transcription task are given in Section 6. Finally,
72 the use of morpho-syntax for confidence measure computation is presented in Section 7.

73 **2. Related works**

74   In this section, related studies that include information about morphology or syntax are presented. Studies
75 specific to the French language are detailed in a second part of the section after an overview of the language
76 specifics.

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[2] By misuse of language, apart from Section 3, where the segmentation problem is discussed, the term "sentence" is used in this paper to name a word sequence delimited by acoustic cues rather than linguistic considerations.
[3] Throughout the paper, we will not limit the notion of part-of-speech to the sole syntactic behavior but rather to syntactic and morphological behavior of lexical items. We will therefore use part-of-speech and morpho-syntax as synonyms.

77   *2.1. Improving language models with linguistic knowledge*

78   Parts-of-speech, in the general sense, are commonly used as morphological and syntactic knowledge that
79   can be associated with words. A popular method to take into account POS relies on class-based *N*-gram mod-
80   els, where each class represents a POS (Jelinek, 1990; Maltese and Mancini, 1992), to compute the probability
81   of a word sequence w_1^n from the possible corresponding classes c_1^n according to
82

$$P_{class}[w_1^n] = \sum_{c_1 \ldots c_n} \prod_{i=1}^{n} P[w_i|c_i]P[c_i|c_{i-N+1}^{i-1}]. \tag{1}$$

84

85   Class-based models are usually linearly interpolated with word-based LMs as both models are complemen-
86   tary in the way the language is considered (Maltese et al., 2001). However, even when combined with word-
87   based LMs, class-based LMs do not usually result in a significant improvement in terms of perplexity or of
88   WER (Weintraub et al., 1996).
89   To get over the limited success obtained with classical class-based LMs, Heeman (1999) proposes an
90   approach based on a 3-gram LM defined over word/tag pairs rather than words, the recognition problem
91   being to find out the best joint word and POS tag sequence. This method results in a significant word error
92   rate reduction. However, due to the drastic increase of entries in the LM, it requires a very large amount
93   of training data and heavily relies on smoothing techniques to make up for the lack of data.
94   Methods resorting to syntactic analyzers have also been developed to include linguistic information. In the
95   case of applications where a constrained grammar can be considered, such as answering questions about a
96   restaurant in a city, probabilistic context-free grammars have been widely used (Jurafsky et al., 1995). Other
97   methods were applied to less constrained domains in order to take into account dependencies through syntac-
98   tic analysis. For instance, Chelba and Jelinek (2000) condition the LM probabilities by the heads of the syn-
99   tactic constituents previously seen, relying on the construction of syntactic trees. Another method developed
100 by Wang et al. (2004) relies on tags with various information, including syntactic constraints between words of
101 a sentence.
102 As far as morphological knowledge is concerned, its interest for ASR has increased a lot in the recent years,
103 particularly for morphologically rich languages such as Turkish, Arabic or Hungarian. The main benefit of
104 morphology is to deal with the high number of out-of-vocabulary words that these languages exhibit with
105 respect to languages such as English. Morphology in ASR often relies on the definition of sub-word units
106 employed in the speech decoding process instead of words. These sub-word units are either obtained from
107 manual resources or, in the most recent studies, inferred by automatic methods. Morphology was successfully
108 applied to agglutinative languages (Kurimo et al., 2006; Hirsimäki et al., 2006); it was also studied for other
109 languages such as English (Huckvale and Fang, 2002). An alternative to resort to morphology relies on the use
110 of sets of features derived from words, instead of words. These features (or factors) can include morphological,
111 syntactic and semantic information (Vergyri et al., 2004).

112 *2.2. Automatic speech recognition for the French language*

113 Though not as morphologically rich as other languages such as Semitic or Finno-Ugrian languages, the
114 French language is a relatively highly inflected language with masculine, feminine, singular and plural
115 forms for adjectives and with many conjugation forms for verbs. However, contrary to other Romance
116 languages such as Spanish or Italian, the inflectional process of a simple form very frequently leads to
117 homophones. For instance, the past participle "*cach*" (hidden, singular masculine form) admits several
118 homophones all derived from the same verb: the singular feminine form "*cachée*", the plural masculine
119 form "*cachés*", the plural feminine form "*cachées*" and the forms of two other modes of the verb, the
120 infinitive "*cacher*" and the indicative present "*cachez*". This particularity increases dramatically the num-
121 ber of homophones in the lexicon of the ASR system, thus complicating transcription. In (Gauvain et al.,
122 1994), it was measured that 75% of the words of an excerpt from a French newspaper had at least one
123 homophone, whereas this number decreased to 23% for an excerpt of the same size from an English
124 newspaper.

125   Different methods were developed for the French language in order to deal with the inflectional process.
126   Class-based language models were conceived by grouping together words associated with a same lemma in
127   a class (El-Bèze and Derouault, 1990) or by automatically deriving classes so as to group together words that
128   are statistically similar (Jardino, 1996). A significant decrease of the perplexity with respect to word-based
129   models was reported but these studies were never tested in a broadcast news automatic transcription system.
130   Using class-based approaches enables LMs to consider long distance dependencies in a sentence, in particular
131   regarding agreements in gender and number. In Lavecchia et al. (2006), a cache-based LM was used along
132   with classes related to the gender and the number of words. In Zitouni et al. (2003), again with the idea of
133   dealing with long span dependencies, linguistic variable length sequences were taken into account in the com-
134   putation of the LM probabilities. These two methods resulted in an improved WER with respect to a classical
135   word-based LM on a French read speech corpus. Finally, a last approach relies on a particular data represen-
136   tation made of several sentence hypotheses, all homophones with the best sentence hypothesis (Béchet et al.,
137   1999; Gauvain et al., 2005). Scoring these homophone hypotheses with a word-based LM and another LM
138   using POS improved the WER from 10.7% to 10.5% to transcribe French broadcast news (Gauvain et al.,
139   2005).
140   All of these methods are mainly related to the high number of homophones in the French language and
141   mostly rely on morphology. However, as mentioned in Section 1, a fair number of errors, due to small gram-
142   matical words, are related to syntax issues.
143   We therefore propose a new approach, relying on morpho-syntactic classes to rerank sentence hypoth-
144   eses, that combines syntax and morphology in a post-processing stage. The method exploits a sentence
145   morpho-syntactic score derived from POS tagging, the MS score being combined with the acoustic and
146   word-level LM scores to rerank the sentence hypotheses. Contrary to many approaches that integrate
147   the MS knowledge in the LM, defining a separate sentence level MS score allows for the use of a
148   long-span model able to deal with dependencies between distant words not taken into account by a
149   word-based 4-gram LM.

3. Morpho-syntactic tagging of automatic transcriptions

151   In order to define a morpho-syntactic score at the sentence level, the first step consists in tagging each sen-
152   tence hypothesis. Morpho-syntactic tagging, which aims at finding out a sequence of MS tags relevant for a
153   given word sequence, is a widely used technique in natural language processing and taggers are now consid-
154   ered reliable enough. However, most experiments were carried out on written text while spoken corpora on the
155   contrary have been seldom studied (Valli and Véronis, 1999). However, oral language has specifics that are
156   likely to disturb taggers, such as repetitions, revisions or fillers, known as disfluencies, or even a possible unu-
157   sual syntax. Moreover, ASR transcripts raise additional difficulties as they are segmented according to acous-
158   tic cues rather than linguistic cues. They also lack punctuation, and, in the case of some ASR systems such as
159   our, capitalization. Transcription errors may also impact text processing techniques. Thus, before using MS
160   information, we demonstrate that such noisy texts can be reliably tagged. This section first describes the meth-
161   odology chosen to implement a POS tagger, and evaluates the relevance of the tagger for automatic
162   transcripts.

3.1. Tagger elaboration

164   The decision to develop a specific tagger was made so as to be more flexible in our experiments, and to limit
165   both the vocabulary and the tag sets. The MS tagger is based on the popular method of hidden Markov model
166   (HMM). Although this technique is quite simple and less recent than others such as support vector machines
167   or maximum entropy models, a study previously showed that their performances were similar (Brants, 2000).
168   HMM-based taggers are also fast enough to tag many hypotheses. The resources (i.e., the lexicon and training
169   corpus) necessary to design the MS tagger are firstly described along with tokenization issues; next, focus is
170   put on the different tag sets tested; the tagger itself is finally presented before describing the post-processing
171   step applied to tag sequences.

3.1.1. Resources

To develop a HMM-based MS tagger, a lexicon which contains the associations between words and their possible tags, and a tagged training corpus to learn the probabilities of POS tag sequences are required.

Concerning the first resource, advantage was taken of the use of a fixed lexicon by the ASR system to restrain the lexicon of the tagger to the sole words of the ASR system vocabulary. This interesting property eliminates the problem of unknown words that would require more complex methods. However, some differences were introduced between the two lexicons, because of their different goals. On the one hand, the lexicon used to transcribe aims at maximizing the lexical coverage with a fixed number of entries, which led to remove capitalization or to add words that belong to locutions, rather than the locutions themselves. On the other hand, the lexicon of the tagger aims at having units that fit the analysis of the grammatical classes of a word sequence. Although automatic transcripts were not capitalized before tagging—which would require to solve ambiguities—20 multi-words were added to the lexicon of the tagger with respect to the ASR system one. Among them were included a few locutions such as "*parce que*" (*because*), "*c'est–dire*" (*that is*), or Latin locutions like "*a priori*". They were selected so as to be automatically identified without risk of errors in resolving ambiguities. Some named entities were also added, such as the names of the French radio channels frequently occurring in the corpus. The addition of these locutions requires to tokenize the transcripts before tagging.

The corpus used to train the MS tagger is a 200,000-word extract from the ESTER training corpus, which consists of French radio broadcast news. This corpus contains prepared and spontaneous speech, and is therefore more relevant than written language corpora to learn a tagger for spoken documents. It has been manually transcribed, including punctuation, by human annotators. A reference tagging was established by manually correcting the output of the Cordial[4] automatic tagger, one of the best taggers available for French which was already successfully applied to spoken documents (Valli and Véronis, 1999; Gendner and Adda-Decker, 2002). The tagged corpus was processed to have a format similar to a transcript: numbers were rewritten into letters, punctuation marks, as well as capitalization, were removed, and the corpus was segmented into breath-groups according to the reference transcripts. A breath-group represents the sequence of words uttered between two breath intakes and is therefore mostly defined according to acoustic cues. Note that the breath-group and sentence segmentations greatly differ: on the 200,000-word excerpt used, only 41.7% of the ends of breath-groups correspond to sentence endings.

3.1.2. Tag sets

Rather than being limited to the main grammatical classes—adverb, adjective, noun, verb, determiner, pronoun, preposition and conjunction—which would have resulted in more robust tagging, the tag set was chosen in order to fit the requirements of ASR for French. As mentioned in Section 2.2, confusions between genders, numbers, tenses or moods are common in French. Consequently, information about gender and number were added for nouns, adjectives and determiners; gender, number and person are associated with pronouns; number, person, mood and tense are indicated for verbs. Besides, in order to train long-span tag-based LMs, the number of selected classes was restrained with respect to very rich tag sets commonly used for French. Thus, distinction between demonstrative and possessive determiners, between ordinal and qualifying adjectives, or information about cases for pronouns were not considered as relevant to correct misrecognized words, and were not taken into account.

Three tag sets were defined. A first one, called $\mathcal{T}_{orig}$ and made of 93 tags, has separate MS tags for each of the main grammatical classes. A second one, named $\mathcal{T}_{red}$, reduces this number of tags in order to focus on morphological information about number and gender. For this reduced tag set, pronouns are split into three categories of tags: personal pronouns share the same information as verbs (person and number), relative pronouns have their own tags, and the other pronouns receive the same inflectional attributes as adjectives and nouns. For verbs, fewer conjugation categories were also considered. Finally, the tag set denoted $\mathcal{T}_{ext}$ extends $\mathcal{T}_{orig}$ by associating the 100 most frequent grammatical words (e.g. "*de*", "*la*", "*le*", "*á*"...) with specific classes. Indeed, these words are problematic for ASR systems—they are short and difficult to transcribe—and for taggers—they are very ambiguous with respect to their grammatical classes. The introduction of explicit infor-

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[4] Distributed by the *Synapse Développement* corporation: http://www.synapse-fr.com/.

220 mation about such words thus appears to be relevant. $\mathcal{T}_{ext}$ also differs from $\mathcal{T}_{orig}$ by its tag set for verbs, intro-
221 ducing specific tags for the difficult to transcribe auxiliary verbs "*avoir*" and "*être*".
222   The tag sets $\mathcal{T}_{orig}$, $\mathcal{T}_{red}$ and $\mathcal{T}_{ext}$ have respectively an average number of tags per word of 1.46, 1.27 and
223 1.33. Table 1 provides the distribution of the two first sets according to the eight main grammatical classes,
224 $\mathcal{T}_{ext}$ having a repartition similar to $\mathcal{T}_{orig}$. In addition to the tags mentioned in Table 1, the three sets have
225 three separate tags for interjections, cardinals and symbols—the last tag corresponding to words such as "*aro-*
226 *base*" (*at sign*) used to name websites.

3.1.3. Tagger

228   The MS tagger is based on HMMs which use a stochastic framework to find out the most probable tag
229 sequence t_1^n for a sentence hypothesis w_1^n according to

$$\hat{t}_1^n = \arg\max_{t_1^n} P[t_1^n|w_1^n] = \arg\max_{t_1^n} P[w_1^n|t_1^n]P[t_1^n], \tag{2}$$

232 where the lexicon provides the correspondence between each word and its possible tags. In order to be prac-
233 tically tractable, the tagging problem is usually approximated (Merialdo, 1994) by
234

$$\hat{t}_1^n = \arg\max_{t_1^n} \prod_{i=1}^{n} P[w_i|t_i]P[t_i|t_{i-N+1}^{i-1}]. \tag{3}$$

237 $P[w_i|t_i]$ is computed from the joint count of the pair (w_i, t_i) in the training corpus and from the number of
238 occurrences of t_i, while $P[t_i|t_{i-N+1}^{i-1}]$ is estimated using back-off and discounting. Finding out the best order
239 N and the best suited discounting technique so as to optimize the tag accuracy was experimentally performed
240 on 40 min of broadcast news transcripts. Absolute discounting was retained for $P[w_i|t_i]$, while the original
241 Kneser–Ney smoothing method (Chen and Goodman, 1998) with an order $N = 3$ was selected for the com-
242 putation of $P[t_i|t_{i-N+1}^{i-1}]$.

3.1.4. Post-processing

244   For N-best list rescoring purposes, it is interesting to post-process the output of the tagger. Indeed, reducing
245 the number of tags in a sentence hypothesis makes it possible to take into account long dependencies with the
246 LM built from MS information. To that end, consecutive cardinals and consecutive proper names are respec-
247 tively grouped into one single cardinal tag and one single proper name tag. Besides, the tag associated with
248 filled pauses, such as "*euh*", is removed. Hence, in Section 4, l will denote the number of word/tag pairs result-
249 ing from the tagging of n words—the difference coming from the tagger specific tokenization—and m the num-
250 ber of tags after post-processing of the tagger output.
251   The different steps of the tagging process, namely tokenization, disambiguation and post-processing (or tag
252 merging), are illustrated in Fig. 2.

3.2. Evaluation

254   A quantitative evaluation of the morpho-syntactic tagger was performed on a 1-h show from the French
255 broadcast news corpus ESTER consisting of 11,300 words. The quality of tagging is measured in terms of

Table 1
Distribution of the number of tags according to the eight main grammatical classes for the two tag sets $\mathcal{T}_{orig}$ and $\mathcal{T}_{red}$, regardless of interjections, cardinals and symbols.

	adverb	adjective	noun	pronoun	verb	determ.	prep.	conj.
$\mathcal{T}_{orig}$	1	4	11	15	51	5	1	2
$\mathcal{T}_{red}$	1	7		4	6	5	1	2

256 tag accuracy. To do so, each tag found by the MS tagger has thus to be compared with the corresponding tag
257 in the reference. We first describe how the tag error rate is computed for automatic transcripts before discuss-
258 ing results and comparing the transcript specific taggers implemented with available taggers originally
259 designed for texts.
260   For automatic transcripts, finding what would be the correct tags can be challenging, even impossible when
261 numerous misrecognized words are present. Evaluating the quality of tagging on an automatic transcript
262 therefore relies on an alignment at the word-level with the reference transcript, the computation of the tag
263 accuracy being limited to words correctly recognized. Fig. 1 illustrates this process by showing the alignment
264 for one breath-group.
265   Table 2, first line, presents results for our HMM-based tagger with the $\mathcal{T}_{orig}$ tag set on manual transcripts
266 (column 1) and on automatic transcripts (column 2) exhibiting a WER of 22.0%. In both cases, the tag accu-
267 racy is over 95% which is comparable to the results usually reported on written corpora. Tagging of the ASR
268 transcript is slightly helped by the absence of out-of-vocabulary words. Nevertheless, the comparable perfor-
269 mance level obtained for both transcripts establishes that MS tagging is reliable, even for texts generated by an
270 ASR system whose recognition errors are likely to jeopardize the tagging of correctly recognized words. The
271 robustness of tagging is mostly explained by the fact that tags are locally assigned. The good performance of
272 the HMM-based tagger remained stable when different tag sets were used with tag accuracies of 96.4% and
273 96.9% for the tag sets $\mathcal{T}_{red}$ and $\mathcal{T}_{ext}$ respectively. In the rest of this section, tag set $\mathcal{T}_{ext}$ is used as it corre-

	REF		HYP
et	COO	et	COO
de	PREP	de	PREP
déterminer	VINF	déterminer	VINF
qui	PMS	qui	*PRI*
y	ADV	–	–
peut	VINDP3S	peut	VINDP3S
être	VINF	être	VINF
dans	PREP	dans	PREP
cette	DETFS	cette	DETFS
administration	NCFS	admiration	NCFS
ou	COO	–	–
qui	PMS	qui	*PRI*
ne	ADV	ne	ADV
peut	VINDP3S	peut	VINDP3S
pas	ADV	pas	ADV
y	ADV	y	ADV
être	VINF	être	VINF

Fig. 1. Alignment of the tagged ASR system output (HYP) with the reference transcript manually tagged (REF). Misrecognized words are underlined and tagging errors are in italics.

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Table 2

Tag accuracy (in %) for three taggers with $\mathscr{T}_{orig}$ measured on a transcript without errors and on a transcript with a measured WER of 22.0%.

Transcription	Manual	Automatic
HMM tagger	95.7	95.7
Naive tagger	90.6	90.7
Cordial	95.0	95.2

sponds to a standard tag set which distinguishes the main grammatical classes and disambiguates the most common grammatical words according to their POS.

As our metric puts aside misrecognized words when evaluating tagging, a manual examination of the tagger behavior for these words was performed. Though MS tags cannot be judged as correct or not on the incorrectly transcribed parts of the corpus, it was noticed that the tagger performed quite well when a few consecutive recognition errors appear. For instance, in the example "*mais les médecins s'avoue un peu désemparés*" (but doctors admits they are a little helpless) where "*avouent*" (admit) was erroneously transcribed as "*avoue*" (admits), the tagger correctly associates the misrecognized word with a singular form, which is relevant to further correct agreement errors. In Fig. 1, it can be seen that the tagger still performs well for the incorrect word "*admiration*" transcribed instead of another noun "*administration*". The second occurrence of the pronoun "*qui*" was classified as erroneously tagged since in the reference it is tagged as an interrogative pronoun rather than as a relative pronoun. However, in the absence of the conjunction "*ou*", omitted in the transcription, the tag assigned by the tagger is correct. Globally, it appears that misrecognized words are not more frequently erroneously tagged than correct words. The most common tagging errors rather concern words difficult to tag such as "*tout*" or "*que*", or locutions and complex terms that were wrongly tokenized, errors that are frequent also in ordinary texts.

The tagger designed for these experiments was compared with two other taggers. The first tagger considered is a naive one that aims at evaluating the difficulty of tagging with respect to the available resources, i.e., the tagged dictionary and the training corpus. The naive tagger associates with each word the most frequent corresponding tag in the training corpus.[5] The second tagger is Cordial. The use of the naive tagger leads to good tag accuracies of over 90% (Table 2, line 2), which are, however, significantly lower than the ones previously obtained. These results show that the use of the HMM reduces tagging errors by more than 50%. The comparison with Cordial[6] (Table 2, last line) shows that the tagger designed for oral transcriptions exhibits performance comparable to that of a standard tagger for the French language.

4. Morpho-syntactic *N*-best list rescoring

As shown in the previous section, POS tagging can be reliably applied to automatic transcripts, thus making it possible to tag each sentence hypothesis in a *N*-best list. In this section, we describe our approach to derive a morpho-syntactic score from a sentence hypothesis based on the corresponding POS tags and to combine this score with the acoustic and word-based LM scores in order to rerank the *N*-best sentence hypotheses.

The choice of *N*-best sentence hypothesis lists, as opposed to word graphs or confusion networks, is dictated by two main motivations. The first reason is that each entry of such lists can be seen as a standard text, thus permitting disambiguation of the possible POS tags. The second reason is that, since only one possible sequence of tags is considered for each sentence, models with a longer context can be used. In word graphs, disambiguation is hardly possible and one must either consider all the possible tag sequences or expand the graph such that each node representing, for instance, a trigram $w_1w_2w_3$ is replaced by all the

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[5] As an illustration, let us note that for the $\mathscr{T}_{orig}$ tag set, 71.0% of the words in the lexicon only have a single possible tag and therefore present no tagging difficulty.

[6] The evaluations with Cordial were performed by considering as correct the confusions between a proper name tag and a common name tag; this was required to fairly compare the taggers, since Cordial relies on capital letters—missing in the analyzed texts—to detect proper names.

possible tag sequences $t_1 t_2 t_3$. In the first case, morpho-syntactic probabilities are averaged over all the possible tag sequences while, in the last case, the size of the word graphs increases drastically with long-span models.

We first define two variants of the morpho-syntactic score before discussing the use of a score function combining acoustic, linguistic and morpho-syntactic information to process *N*-best sentence hypothesis lists. Results are reported in Section 6.

4.1. Combined score function

Let us denote a sentence hypothesis w_1^n, and t_1^m the most likely tag sequence as determined by morpho-syntactic tagging (including tokenization and post-processing of the tag sequence as discussed in Section 3.1.4), the probability of the tag sequence being given by

$$P[t_1^m] \approx \prod_{i=1}^{m} P[t_i | t_{i-N+1}^{i-1}].$$

(4)

Note that the number *m* of tags may differ from the number *n* of words due to the tokenization of the word sequence and the post-processing of the tags. It is also important to note that the order of the model used to compute (4) does not need to be the same as the one of the model used in (3) for disambiguation of the tag sequence and, in practice, different orders will be used.

Most ASR systems evaluate the relevance of each sentence hypothesis w_1^n given the acoustic input y_1^t from the probabilities $P(y_1^t | w_1^n)$ and $P[w_1^n]$ respectively computed by the acoustic model and the language model. In practice, the two scores are linearly combined in the log-domain according to

$$s_{\mathrm{orig}}(w_1^n) = \ln P(y_1^t | w_1^n) + \alpha \ln P[w_1^n] + \gamma n,$$

(5)

where α is the LM scale factor and γ a word insertion penalty. This baseline score functions is also classically used for *N*-best list or word graphs post-processing. To account for morpho-syntactic knowledge, we extend this global sentence score by extending the linear combination to include the morpho-syntactic score $P[t_1^m]$, i.e.,

$$s_1(w_1^n) = \ln P(y_1^t | w_1^n) + \alpha \ln P[w_1^n] + \beta \ln P[t_1^m] + \gamma n,$$

(6)

where β is the POS scale factor. We propose a variant of the MS score (4) which takes into account the lexical probabilities $P[w_i | t_i]$ that are traditionally incorporated in class-based LMs,[7] formally given by

$$s_2(w_1^n) = \ln P(y_1^t | w_1^n) + \alpha \ln P[w_1^n] + \beta \left(\ln P[t_1^m] + \sum_{i=1}^{l} \ln P[w_i' | t_i'] \right) + \gamma n,$$

(7)

where $w_1'^l$ and $t_1'^l$ denote respectively the sequence of words after the tokenization step required by MS tagging and the corresponding tag sequence before the post-processing step (see Section 3.1.4 for details on the post-processing step of the tagger output).

Based on one of the two sentence-level score functions, as defined in either (6) or (7), *N*-best lists can be rescored using various criteria. Three criteria, namely maximum *a posteriori* (MAP), minimum expected word error rate (Stolcke et al., 1997), and consensus decoding on *N*-best lists (Mangu et al., 2000) were studied in this paper.

4.2. Decoding criteria

In the context of *N*-best list rescoring, maximum *a posteriori* decoding aims at finding out the most likely sentence hypothesis given the acoustic features y_1^t, which simply consists in selecting the sentence hypothesis $w^{(i)}$ whose score $s(w^{(i)})$ is maximum, i.e.,

---

[7] See (1) in Section 2.1

$$\widehat{w} = \arg\max_{w^{(i)}} s(w^{(i)}). \tag{8}$$

Usually, the sentence score is given by (5). To account for morpho-syntactic information, we propose to use one of the two variants (6) or (7) for $s(w^{(j)})$ instead of (5).

The maximum *a posteriori* criterion, which operates at the sentence level, aims at minimizing the sentence error rate. However, in many cases, one is rather interested in minimizing the word error rate. To do so, several alternate decoding criteria have been proposed, the most popular ones being explicit WER minimization and consensus decoding. The explicit word error rate minimization criterion (Stolcke et al., 1997) consists in finding out the sentence in a *N*-best list that minimizes the *a posteriori* expectation of the word error rate. Consensus decoding (Mangu et al., 2000) exploits a multiple alignment of the entries in the *N*-best list, represented as a confusion network. Both criteria rely on the computation of the posterior probability

$$P[w^{(i)}|y_1^t] = \frac{e^{s(w^{(i)})/z}}{\sum_j e^{s(w^{(j)})/z}}, \tag{9}$$

where z is a normalization factor. As for the MAP criterion, the sentence-level score denoted $s()$ in the above equation can be given by either (5) or one of the two variants including morpho-syntactic knowledge.

Clearly, taking into account morpho-syntax as we propose is first and foremost beneficial at the sentence level, one of the goals of morpho-syntax being the generation of more grammatical sentence hypotheses. However, the two word error minimization criteria rely on sentence posteriors computed from sentence-level scores. It is therefore interesting to measure how morpho-syntactic knowledge helps word error minimization criteria which can be detrimental to the sentence error rate. Moreover, if explicit WER minimization ends up reranking a *N*-best list, consensus decoding can provide new sentence hypotheses not originally in the *N*-best list and often less grammatical—as confirmed by the usually higher sentence error rates obtained with consensus decoding. As a consequence, the proposed combined scores with POS knowledge might impact differently the two criteria.

Experimental results are given in Section 6, after a description of the experimental setup.

5. Experimental setup

This section describes how transcription is performed and presents the corpus used. Details are also provided about the implementation of two methods from the literature that use morpho-syntactic information, namely class-based *N*-gram model and homophone lists reranking, to which we compare.

5.1. The ASR system

The ASR system used in all our experiments is the IRENE broadcast news transcription system (Gravier et al., 2005), jointly developed by IRISA and Telecom Paris for the ESTER broadcast news transcription evaluation campaign (Galliano et al., 2005). An overview of the system architecture is given in Fig. 2 and details are given in the next paragraphs.

The pre-processing step consists in detecting regions containing speech which are then segmented into breath-groups—abusively called *sentence* in the sequel—based on fillers as provided by phonetic decoding. Let us stress the fact that sentence segmentation does not rely on any syntactic and grammatical considerations, though breath intakes and grammar are somewhat related. A partitioning into speaker turns is also performed in the pre-processing step. To avoid problems due to segmentation errors, experiments for this paper were carried out with a manual pre-processing but results with automatic pre-processing are reported at the end of Section 6.2.

The speech decoding step is carried out in three passes. A first pass with fairly simple context-independent acoustic models and a 3-gram word-based LM aims at generating large word graphs. These word graphs are then rescored with more complex context-dependent acoustic models and a 4-gram LM. Rescoring word graphs is based on a MAP decoding criterion (without the use of morpho-syntax) where the maximization is limited to the set of word sequences encoded in the word graph, thus making the use of more complex mod-
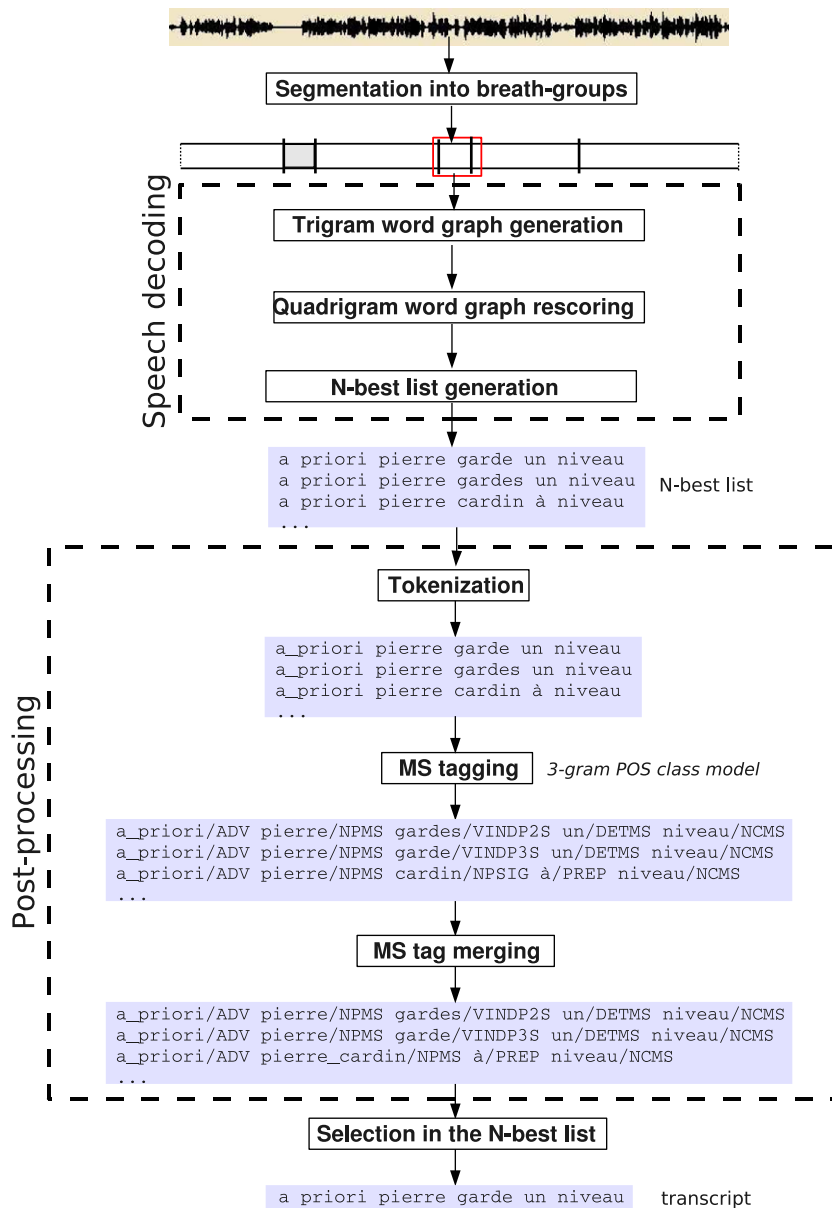
Fig. 2. Flowchart of the transcription process illustrating the three steps (pre-processing, speech decoding and *N*-best list post-processing). The post-processing step is in turn divided into the tokenization, MS tagging and tag merging steps necessary for *N*-best list decoding with MS information.

403 els tractable. Finally, based on the transcription from the second pass and the speaker partition obtained in
404 the segmentation step, the acoustic models are adapted for each speaker and final word graphs are obtained by
405 rescoring the initial word graphs with speaker-adapted acoustic models. *N*-best lists are extracted from the
406 final word graphs. For speech recognition purposes, lists of 100 hypotheses were used as we observed that
407 increasing the list size to 1000 did not yield any improvement. However, for confidence measure computation
408 as described in Section 7, 1000 sentence candidates are considered.
409   In the post-processing step of the recognition process, each entry in the *N*-best lists is tagged with a 3-gram
410 class model before rescoring. The various steps of the tagging process (tokenization, tagging and merging—see
411 Section 3 for details) are depicted in Fig. 2.

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Table 3
Parts of the ESTER corpus used.

	Training	Development	test-a	test-b
Duration	72 h 40	4 h	4 h	10 h
Period	1998–2003	2003	2003	2004

5.2. Data description

As previously mentioned, experiments described in this article were carried out on the ESTER French broadcast news transcription task. A corpus of about 100 h of manually transcribed data was used and divided into four parts (Table 3). A large part was reserved for the purpose of acoustic and language model training, 20 h of which—i.e., 200,000 words—were tagged and used for the training of the N-gram tag-based models.[8] The 4-gram word-based language model, used as well for the two last decoding passes as for the post-processing of the N-best lists, was obtained by interpolating a LM estimated on 1 million words from the reference transcripts of the training set with a LM estimated from 350 million words from the French newspaper Le Monde.

A set of 4 h from four different broadcasters makes up a development set on which parameters were optimized. Another set of 4 h (test-a), recorded from the same broadcasters and during the same period as the training and the development corpora, forms a first test corpus. A last set of 10 h (test-b) was used for the test; it contains 8 h from the same four radio channels as the other sets and 2 h from two new broadcasters. On the test-a set, the baseline WER is 19.7% and the 100-best list oracle WER[9] is 11.0%.

5.3. Class-based morpho-syntactic language model

As already mentioned in Section 2, resorting to classical class-based LMs is a common approach to take into account POS in ASR (Jelinek, 1990; Maltese and Mancini, 1992; Maltese et al., 2001). When using these models, each class corresponds to a grammatical class and the probability of a word sequence is computed according to (1). Generally, class-based LMs are used in combination with a word-based LM thanks to linear interpolation according to

$$P[w_1^n] = \prod_{i=1}^{n} \left[\lambda P_{word}[w_i|w_1^{i-1}] + (1 - \lambda)P_{class}[w_i|w_1^{i-1}] \right], \tag{10}$$

where λ is the interpolation coefficient, and P_{word} and P_{class} are the probabilities computed respectively by a word-based LM—typically a N-gram LM—and a class-based LM. The conditional probabilities $P_{class}[w_i|w_1^{i-1}]$ are obtained by the class-based LM thanks to

$$P_{class}[w_i|w_1^{i-1}] = \frac{P_{class}[w_1^i]}{P_{class}[w_1^{i-1}]}, \tag{11}$$

where $P_{class}[w_1^i]$ is given by (1).

The interpolated language model score defined by (10) comes as a replacement for the standard word-based language in (5) for N-best list rescoring. Note that in this case, no tagging, i.e., disambiguation, is performed.

5.4. Homophone N-best list generation

We emphasized in the introduction the interest of MS information to correct, among others, gender and number agreement errors for homophones. Based on this idea, an alternative data representation, lattice of homophones, has been previously suggested to take into account POS knowledge (Béchet et al., 1999; Gau-

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[8] This corpus is actually the same as the one used to train the tagger.
[9] The N-best list oracle WER is obtained by selecting a posteriori the sentence hypothesis with the smallest number of errors in each N-best list.
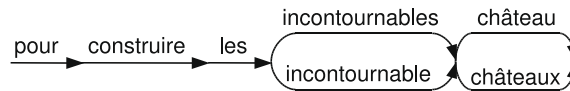
Fig. 3. Homophone expansion for the example "*pour construire les incontournables château*".

447 vain et al., 2005). In the framework of *N*-best list rescoring, we implemented this method with homophone *N*-
448 best lists obtained by expanding the best hypothesis as provided by the ASR system with homophones.
449   However, not all the possible expansions were considered. Firstly, the number of homophones for a given
450 word can be huge. Secondly, as the homophone representation aims at correcting agreement errors, the inter-
451 est of homophone expansion is restricted to the words that are likely to be concerned by such errors, i.e., those
452 that can be inflected. Consequently, the expansion of word hypotheses is limited to adjectives, nouns, verbs
453 and personal pronouns. Besides, the list of homophones for a given word is limited to those words sharing
454 the same lemma, i.e., that differ only according to their inflection. Fig. 3 illustrates the process for the sentence
455 hypothesis "*pour construire les incontournables château*",[10] with an agreement error on "*château*". Among the
456 three words that can be expanded, no homophone was found in the dictionary for the verb "*construire*", the
457 singular form of the adjective "*incontournables*" was added while the noun "*château*" was expanded with its
458 homophone plural form "*châteaux*".
459   The size of homophone *N*-best lists ranges from a few sentences to several thousands, with an average size
460 of 554 and a median size of 24. On the *test-a* set, the oracle WER of the homophone *N*-best lists is 17.7%,
461 much higher than the 11.0% achieved for the standard 100-best list.

6. Transcription results

463   Experimental results for speech recognition are given in this section. In a first part, preliminary experiments
464 aiming at comparing the tag sets and setting the parameters of our method are presented. The three decoding
465 criteria are then compared before analyzing the results from a qualitative point of view. A discussion on the
466 extension of the method to other ASR systems and languages is finally given.

6.1. Parametrization

468   One of the first choices that needs to be made concerns the order of the POS LM. Interestingly, it was
469 observed in early experiments with various tag sets that transcripts are improved with a POS 4-gram model
470 which demonstrates that the POS information is complementary to the linguistic information already embed-
471 ded in the word-based LM model. The best compromise was obtained for $\mathcal{T}_{ext}$ with a 7-gram model for the
472 computation of the morpho-syntactic score with a Kneser–Ney smoothing technique. An order of 7 is used in
473 the remaining experiments.
474   In (6) or (7), the various scores are scaled with an appropriate factor. Fig. 4 plots the WER on the devel-
475 opment data as a function of the POS scale factor β for the tag set $\mathcal{T}_{ext}$, all other parameters being optimized
476 separately for each value of β. The MAP decoding criterion is used in these experiments with the MS score (6).
477 These results show a clear decrease of the WER for values of β between 1 and 7.
478   As discussed in Section 3.1.2, several tag sets can be envisaged. Results are given in Table 4 for the three tag
479 sets where an absolute decrease of at least 0.5 of the WER was obtained with respect to the baseline system
480 without morpho-syntax, whatever the tag set used. However, the best performance was obtained with the
481 extended tag set $\mathcal{T}_{ext}$, which demonstrates the interest of information about grammatical classes and morpho-
482 logical knowledge, as well as that of the specific tags for the most frequent grammatical words. In all of the
483 remaining experiments, the extended tag set will be used with a 7-gram model.

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[10] The hypothesized sentence which translates into "*to build the inevitable castle*" exhibits an agreement error between "*les incontournables*" (plural form of the words "*the inevitable*") and "*chateau*" (singular form of the word castle).

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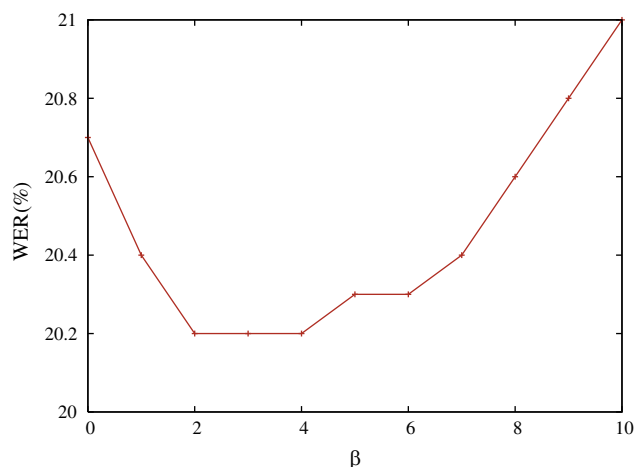

Fig. 4. WER as a function of the POS scale factor β on the development data with a MAP decoding criterion, the score $s_1(w_1^n)$ and the $\mathcal{T}_{\text{ext}}$ tag set.

Table 4
WER (%) measured on both test corpora from 100-best lists with several tag sets. The reranking of N-best lists was done with $s_1(w_1^n)$ score and with a MAP criterion.

	Baseline	$\mathcal{T}_{\text{orig}}$	$\mathcal{T}_{\text{red}}$	$\mathcal{T}_{\text{ext}}$
test-a	19.7	19.1	19.2	19.0
test-b	24.7	24.2	24.2	24.0

6.2. Comparison of several approaches

We first compare several score functions for reranking N-best lists, whether standard or homophone. We then compare the three decoding criteria before discussing the significance of the results.

Results for the two score functions defined in this paper are presented in Table 5 for the MAP decoding criterion, where they are compared with a class-based LM approach and with homophone N-best list reranking. The first column reports the WER for the baseline system where no MS information is used. Results for N-best list reranking are given in columns 2–4 respectively with $s_1(w_1^n)$, $s_2(w_1^n)$ and with a LM resulting from the interpolation of the word-level and POS-level LMs (see Section 5.3 for details). Finally, results for our method on homophone N-best list reranking, rather than standard 100-best list reranking, are presented in the last two columns for the two score functions.

The comparison of the different approaches first exhibits an absolute decrease of 0.7 for 100-best lists with $s_1(w_1^n)$ with respect to the baseline system. Using $s_2(w_1^n)$ instead leads to a more important decrease. Interestingly, we noticed that the two score functions only increase the WER for 1 out of 7 shows of *test-a* and reduce the WER for all the 18 shows of *test-b*. Besides, the improvement achieved resorting to a classical class-based LM linearly interpolated with a word-based LM is significantly less than that achieved with our method, in particular with the score function $s_2(w_1^n)$. Finally, reranking homophone N-best lists results in a limited

Table 5
WER (%) measured on both test corpora from 100-best lists or homophone extensions, according to different scores and with MAP decoding.

	Baseline	100-best lists			Homophone ext.	
	$s_{\text{orig}}(w_1^n)$	$s_1(w_1^n)$	$s_2(w_1^n)$	Class-based LM	$s_1(w_1^n)$	$s_2(w_1^n)$
test-a	19.7	19.0	18.8	19.1	19.4	19.4
test-b	24.7	24.0	23.9	24.2	24.4	24.4

500 WER gain which indicates that morpho-syntactic N-best list rescoring with our method is able to correct
501 errors others than those on homophones. This fact will be discussed in more details at the end of the current
502 section.
503   Results for N-best list rescoring with the three decoding criteria considered in this paper, namely MAP,
504 explicit WER minimization and consensus, are given in Table 6 for the score function $s_2(w_1^n)$. The two word
505 error minimization criteria clearly benefit from a sentence score function that includes morpho-syntactic
506 knowledge though larger gains are achieved for the maximum *a posteriori* criterion. Consensus decoding using
507 posteriors that include MS information yielded the best performance.
508   Statistical tests were carried out to measure how significant are the improvements observed, assuming inde-
509 pendence of the errors across sentences. First, both the paired t-test and the paired Wilcoxon test, through
510 p-values smaller than 10^{-5}, demonstrate that the scores $s_1(w_1^n)$ or $s_2(w_1^n)$ significantly improve the WER by
511 taking into account morpho-syntax with respect to the baseline system, for the two test corpora and for all
512 the decoding criteria. Regarding the comparison of the $s_1(w_1^n)$ and $s_2(w_1^n)$ scores with the class-based LM,
513 results are not significantly different on the *test-a* corpus. On the *test-b* corpus, p-values lower than
514 5×10^{-2} and 2×10^{-3} for $s_1(w_1^n)$ and $s_2(w_1^n)$ respectively show a mild significance. Finally, improvements with
515 respect to homophone N-best list reranking are significant for the two test sets with p-values smaller than 10^{-4}.

6.3. Qualitative analysis of the results

517   In this discussion, we provide some qualitative insights on the results, regarding the robustness to speaking
518 style and the typology of the errors corrected.
519   A first question raised by these experiments concerns the robustness of the method to non prepared speech,
520 for which syntax is relaxed. Word error rates were computed separately on a short extract of 3650 words, con-
521 taining interviews with numerous disfluencies. On this extract, the baseline WER of 44.9% is reduced to 43.7%
522 with $s_1(w_1^n)$ and to 43.6% with $s_2(w_1^n)$ using the MAP criterion. This 3% relative improvement, close to the 4%
523 relative improvement obtained on the entire *test-a* set, demonstrates that the method is quite robust to speak-
524 ing style.
525   As far as the recovered errors are concerned, we observed that, as expected, many agreement errors were
526 corrected, such as the confusion about number for the noun "*minorité*" in the first example in Fig. 5. More-
527 over, we also noticed that hypotheses generated with the use of morpho-syntax tend to be more grammatical.
528 The second example in Fig. 5 illustrates this fact where the ungrammatical transcription for the baseline sys-
529 tem becomes correct after changing the grammatical words "*aussi*" and "*qui*" into "*si*" and "*qu'il*". This phe-
530 nomenon is assessed by the significant reduction of the sentence error rates obtained when taking into account
531 MS information (Table 7, last line).
532   In order to measure quantitatively how error reductions due to MS affect words according to their gram-
533 matical class, two new metrics were defined: the lemma error rate (LER) and the lemma error rate on lexical
534 words (LER$_{lex}$). The basic idea of these metrics is to ignore errors about inflections and, eventually, about
535 grammatical words. The LER is a straightforward extension of the WER where the error rate is computed
536 over lemmas rather than words, thus ignoring inflection errors. A comparison between the WER and the
537 LER therefore roughly indicates the proportion of misrecognized words due to agreement errors. In the first
538 example in Fig. 5, the LER would be the same for the two hypotheses since "*minorité*" (minority) and "*minor-
539 ités*" (minorities) share the same lemma. The LER limited to lexical words limits the computation of the LER
540 to nouns, verbs and adjectives, therefore measuring whether morpho-syntax rather affects grammatical or lex-
541 ical words. For instance, in the second example of Fig. 5, the computation of LER$_{lex}$ would be limited to the
542 only lexical word of the hypothesis, i.e., "*puissant*" (powerful).

Table 6

WER (%) measured on both test corpora with three decoding criteria.

	test-a			test-b		
	MAP	Min. WE	Cons.	MAP	Min. WE	Cons.
Without MS	19.7	19.5	19.4	24.7	24.3	24.0
With MS	18.8	18.7	18.7	23.9	23.6	23.5

```
w/o MS: à part quelques MINORITÉ

w/  MS: à part quelques minorités

w/o MS: AUSSI puissant *** QUI soit

w/  MS: si    puissant qu' il  soit
```

Fig. 5. Two breath-groups transcribed without or with the use of morpho-syntax. Deletion errors are indicated by ∗ while misrecognized words are written in capitals. The reference for the first example translates into "*apart from some minority*" w/o MS and "*apart from some minorities*" w/ MS. For the second example, the corresponding translations are respectively "*as powerful who may be*" and "*as powerful as he may be*".

Table 7

Word error rate, lemma error rates and sentence error rate (SER) on the *test-b* corpus (MAP criterion).

	test-b		
	Baseline	$s_1(w_1^n)$	$s_2(w_1^n)$
WER	24.7	24.0	23.9
LER	21.8	21.4	21.3
LER$_{lex}$	22.9	22.6	21.8
SER	70.5	68.8	69.1

543   Computing the two lemma error rates requires that the reference and automatic transcripts be tagged and
544 lemmatized, which was done automatically using our tagger and FLEMM (Namer, 2000). Note that the auto-
545 matic lemmatization step is error-prone thus introducing a bias in the LER computation. However, our tagger
546 performs well on broadcast news, as shown in Section 3.2, and numerous tagging errors affect grammatical
547 words, which are easy to lemmatize. For LER$_{lex}$, the reference and ASR transcripts are restricted to nouns,
548 verbs and adjectives before aligning the two. Auxiliaries and modal verbs are also discarded.
549   Results obtained on the *test-b* corpus according to the two lemma error rates are given in lines 2 and 3 of
550 Table 7. The comparison between the WER and the LER shows that for the baseline system, 2.9% of the
551 words (24.7–21.8) are correct according to their lemma, but have a wrong inflection. This figure is reduced
552 to 2.6% using morpho-syntax, which indicates that this knowledge corrects some agreement errors. The use
553 of morpho-syntax leads to an absolute decrease of the WER by 0.7 or 0.8 depending on the score function
554 used, which translates into an absolute decrease of the LER by 0.4 or 0.5 point respectively. This suggests that
555 globally around 40% of the gain due to morpho-syntax are related to inflection errors and 60% correspond to
556 changes of lemmas. These results also explain why homophone *N*-best lists, for which the use of morpho-syn-
557 tax is limited to inflections, yield less gain than regular *N*-best lists.
558   Interestingly, a study of LER$_{lex}$ reveals a different influence of morpho-syntactic information according to
559 the score function used. Indeed, $s_2(w_1^n)$ leads to a more significant decrease of LER$_{lex}$ than $s_1(w_1^n)$. This indi-
560 cates that $s_2(w_1^n)$ tends to modify the lemmas of content words, while $s_1(w_1^n)$ acts more upon grammatical
561 words. The greater effect of $s_2(w_1^n)$—that takes into account the intra-class probabilities $P(w_i|t_i)$—on content
562 words is related to its inclination to select words associated with their most frequent tag.

563 *6.4. Discussion*

564   Several comments can be added at this point regarding the portability of the method to different ASR
565 systems.
566   First of all, let us recall that a manual sentence segmentation was used in the experiments presented so far.
567 Automatic sentence segmentation, by making segmenting based on less syntactic considerations than human
568 might be detrimental to MS post-processing. However, the proposed approach was recently used in the

569 ESTER 2 radio broadcasts transcription evaluation campaign[11] (Galliano et al., 2009) with a fully automatic
570 system where a relative improvement ranging from 1% to 3% relative, depending on the show, was achieved.
571 The fact that the relative improvement is slightly less than what was reported in this paper is mainly due to the
572 fact that the vocabulary of the ASR system has changed, that of the tagger no longer matching that of the
573 recognition system. Hence, automatic segmentation into breath-group based on fillers detected by a phone-
574 loop does not impact morpho-syntactic rescoring as proposed in this paper.

575   Secondly, the ASR system used in this study though based on standard HMM-based techniques is not a
576 state-of-the-art system for which lower WER can be expected. Even if the ASR system used in these experi-
577 ments is not a state-of-the-art one, we believe that the proposed approach would also benefit to some extent to
578 a such system. The higher error rates of our system are due to two main reasons: the acoustic model is far from
579 the state-of-the-art (no cross-word triphones in the first pass, no telephone bandwidth model, neither CMLLR
580 nor SAT, etc.) and the amount of training data for the language model is limited (less than 400M words).
581 However, many of the errors targeted by our MS rescoring method are still present in state-of-the-art systems,
582 though to a lesser extent. A good example is given by the errors on homophones (Gauvain et al., 2005), clearly
583 related to the language model. Errors on short grammatical words might be reduced with better acoustic mod-
584 eling but will still be present in the transcripts. On top of that, morpho-syntactic post-processing is carried out
585 with a 7-gram class-based LM whose span is longer than that of the 4-gram word-level LMs used in state-of-
586 the-art systems. Clearly, a long-span model should benefit to a system even if the LM has been trained on
587 more data.

588   Finally, as emphasized in the previous section, the use of morpho-syntax is far from being limited to inflec-
589 tion errors as about 60% of the errors that recovered result in a change of lemma. This suggests that less mor-
590 phologically rich languages can benefit from MS information. Furthermore, in complementary experiments
591 not reported in this paper, we successfully applied our method to rerank N-best lists generated by an on-line
592 handwriting recognition system for the English language (Quiniou et al., 2005). Though not directly compa-
593 rable to the speech recognition field, this last result suggests that morpho-syntactic post-processing of N-best
594 lists should be of interest for less inflectional languages.

595 **7. Confidence measures**

596   The experiments reported in the previous section demonstrated, both quantitatively and qualitatively, the
597 interest of morpho-syntax to significantly improve ASR transcripts by post-processing N-best lists. In partic-
598 ular, we showed that morpho-syntactic information is effective to compute the sentence posteriors that are
599 used in decoding with WER minimization criteria. These same sentence posteriors on N-best lists are also
600 commonly used for the computation of confidence measures (Rueber, 1997) which should therefore also ben-
601 efit from morpho-syntax information.

602   In this section, the appropriateness of morpho-syntax to detect recognition errors is first highlighted before
603 evaluating confidence measures that exploit sentence posteriors computed over the previously defined score
604 functions combining acoustic, language model and morpho-syntactic knowledge.

605 *7.1. Interest of morpho-syntax to detect errors*

606   To assess the interest of a morpho-syntactic score for confidence measures, the local scores $P\left(t_i|t_{i-6}^{i-1}\right)$ and
607 $P\left(w_i|w_{i-3}^{i-1}\right)$ of the 7-gram tag-based LM and of the 4-gram word-based LM were plotted for a few breath-
608 groups. These plots reveal an interesting property of the tag-based LM, as illustrated in Fig. 6. Indeed, in
609 the case of the tag-based LM, the local scores are significantly lower for erroneous words than for correct ones
610 while with the word-based LM score, low local score were observed on correct words. This difference can be
611 explained by the more frequent use of smoothing or back-off for the word-based LM, over a vocabulary of
612 64,000 words, than for the POS LM over a few hundred tags.
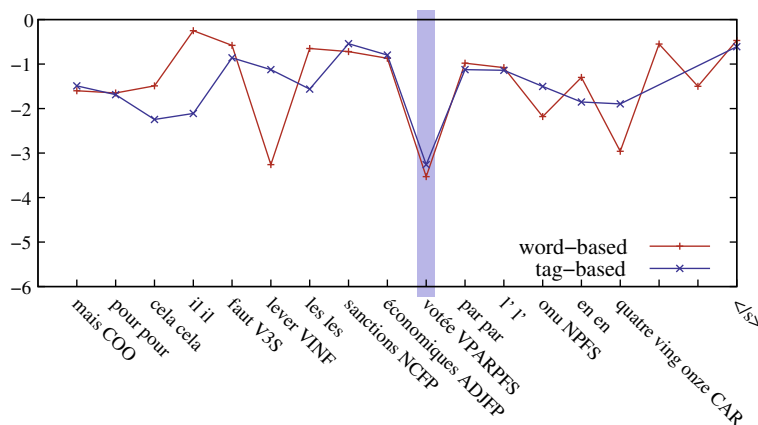

Fig. 6. Conditional log-probabilities $\ln P(t_i|t_{i-6}^{i-1})$ and $\ln P(w_i|w_{i-3}^{i-1})$ computed for each word (tag set $= \mathcal{T}_{\text{ext}}$). The shaded area over the past participle "*votée*" indicates an error.

The interest of such a property was assessed quantitatively by comparing the local scores, or a combination of the local scores, to a threshold in order to determine whether a word is correct or not. When considering solely the word-based LM, a word w_i is considered as erroneous if

$$\ln P(w_i|w_{i-3}^{i-1}) \leqslant \mu + a\sigma, \tag{12}$$

where μ and σ are respectively the mean and standard deviation of the LM log-probabilities over the whole sentence. One can also consider the word-based and POS-based LM jointly and decide that a word is erroneous if

$$\ln P(w_i|w_{i-3}^{i-1}) + \ln P(t_i|t_{i-6}^{i-1}) \leqslant \mu' + a\sigma', \tag{13}$$

where μ' and σ' are defined in a similar way as for (12).

Recall and precision curves obtained by varying the parameter a are given in Fig. 7 on a 30 min excerpt from the *test-a* corpus, where recall is the proportion of correct words detected as such and precision is the proportion of correct words in the set of words whose score is above the threshold. To better study the interest of morpho-syntax for agreement errors, two tasks are considered. In task 1, all words are considered while in task 2, only words whose transcription exhibits either an agreement error or a confusion between past parti-
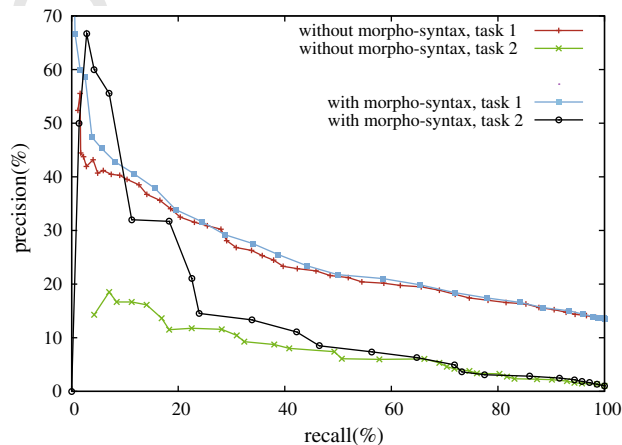

Fig. 7. Recall-precision curves for the detection of transcription errors by a word-based LM and a tag-based LM (tag set $= \mathcal{T}_{\text{ext}}$).

630 ciple and infinitive are considered. The low precision for the second task is due to the fact that, apart for very
631 low values of the POS log-probabilities, words found as erroneous are often detected as such for reasons not
632 related to agreement errors or confusion between past participle and infinitive. In all cases, the use of morpho-
633 syntactic knowledge enables the detection method to improve at all recall values, especially for task 2. Nev-
634 ertheless, this improvement is mainly observed for low recall values, corresponding to low values of a. This
635 indicates that when the two LMs face a sequence not very frequent in the training corpus, the decision of
636 the tag-based LM is more reliable than the one of the word-based LM.

637 7.2. Confidence measure computation

638 The previous results demonstrate that morpho-syntactic information can help to detect errors. We therefore
639 study the impact of scores including morpho-syntactic information for confidence measure computation from
640 N-best lists.
641 Confidence measures are computed either from the N-best lists after reranking by MAP decoding or from
642 the confusion networks built for consensus decoding. When MAP decoding is used, the confidence measures
643 are computed from the sentence posterior probabilities as in (Rueber, 1997). The idea is to align each alternate
644 sentence hypothesis with the best one. The confidence measure for a word $w_i = w$ in the best sentence hypoth-
645 esis is the sum of the sentence posterior probabilities over all the sentences that contain the same word w
646 aligned with w_i. When consensus decoding is used, confidence measures are directly obtained from the highest
647 posterior probability for each slot in the confusion network.
648 Normalized cross entropy values (NCE) (Siu and Gish, 1999), which measure the mutual information
649 between correctly recognized words and the computed confidence measures with respect to an optimal con-
650 stant confidence measure, are reported in Table 8 for MAP and consensus decoding on the two test sets, using
651 the score function $s_2(w_1^n)$. The word error rates for the various configurations tested, namely MAP/consensus
652 decoding with/without morpho-syntax are reported on the first line of the table for each corpus. The next two
653 lines report the NCE obtained when computing confidence measures respectively without and with morpho-
654 syntactic knowledge. In all cases, using morpho-syntax clearly improves confidence measures, thus indicating
655 that the MS score provides additional syntactic information not sufficiently captured by the word-based LM.
656 It can also be noted that the NCE is lower for consensus decoding than for MAP decoding. This is due to the
657 fact that the parameters, and in particular the scale factor z in (9), are optimized to maximize the NCE in the
658 second case, since different parameters can be used for rescoring and for confidence measure computation in
659 MAP decoding.
660 The detection error trade-off curves, such as the one plotted in Fig. 8 on the development corpus with MAP
661 decoding, confirms the interest of morpho-syntax for confidence measures. In particular, the observed
662 improvement mainly concerns the high confidence measure values, i.e., when the words most likely misrecog-
663 nized are discarded. This phenomenon is in fact correlated with the improvements observed previously in
664 Fig. 7 for decisions upon recognition errors with low threshold values.

Table 8
WER and normalized cross entropy measured on the two test corpora for two decoding criteria, with and without MS information.

	MAP decoding		Consensus decoding	
	w/o MS	w/ MS	w/o MS	w/ MS
test-a				
WER	19.7%	18.7%	19.4%	18.6%
NCE w/o MS	0.307	0.265	0.198	–
NCE w/ MS	0.326	0.288	–	0.211
test-b				
WER	24.7%	23.9%	24.0%	23.5%
NCE w/o MS	0.288	0.263	0.254	–
NCE w/ MS	0.305	0.275	–	0.258

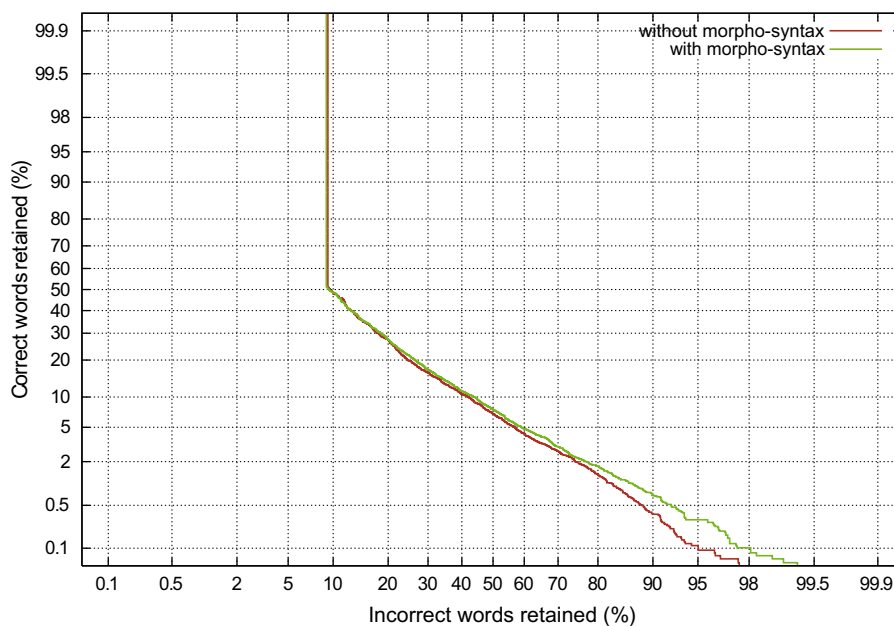*S. Huet et al. / Computer Speech and Language xxx (2009) xxx–xxx*

Fig. 8. Detection error trade-off curves obtained on the development corpus for a transcription using MAP reranking with morpho-syntax (WER = 20.2%, NCE without MS = 0.223, NCE with MS = 0.241).

8. Conclusion

We presented a study on the integration of morpho-syntactic knowledge into ASR systems and validated it for the French language. Unlike previous works that introduced morpho-syntactic knowledge at the LM level by interpolation of a class-based N-gram model with a word-based one, we combine the acoustic, LM and morpho-syntactic log-scores at the sentence level. The resulting score function was found to significantly and consistently decrease the WER both with maximum *a posteriori* and explicit WER minimization decoding criteria. Besides, sentence posterior probabilities incorporating morpho-syntactic knowledge were shown to be relevant to improve confidence measures.

An analysis of the modifications induced by the use of morpho-syntactic information in transcription, as well as the observed decrease of the sentence error rate, show that this kind of information generates more grammatical transcripts. This result is particularly interesting since more grammatical transcripts should facilitate the use of natural language processing techniques for high level semantic analysis. Moreover, the study of the lemma error rate shows that, if a significant proportion of the errors corrected is related to gender and number agreements, or conjugation mistakes, morpho-syntax globally reduces the number of errors on lemmas. This last results, along with complementary experiments, suggest that the method should extend to other, less inflected, languages such as English. However, further experiments remain to be done with other languages to measure to what extent MS information can improve transcription.

Let us conclude by emphasizing the fact that the general idea of combining log-scores at the sentence level to rescore N-best lists can readily be extended to other knowledge sources such as semantics or advanced syntax. For example, a semantic score indicating whether the words in the sentence are semantically related could be considered. As far as syntax is concerned, deriving from a full syntactic parsing a score that reflects the appropriateness of the chunks in a sentence might be a way to consider syntax in an ASR system without the burden of integrating a complex algorithm such as a parser at the decoder level.

Acknowledgments

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