## Detection of sentence modality on French automatic speech-to-text transcriptions

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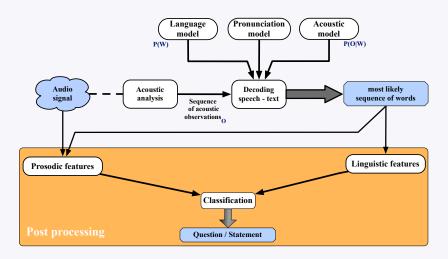




- Context
- 2 Approach
- 3 Experiments
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#### Context

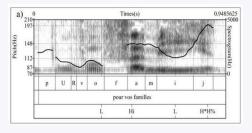
**Objective**: state from the automatic transcription if the sentence is a question or a statement



#### Context

#### Two types of questions

- expressed with interrogative forms
  - \* qu'est ce qu'on doit comprendre ?
  - \* est ce que vous souhaitez une confrontation ?
  - \* quelles sont les grandes annonces hein à attendre ?
- perceived as questions only through the intonation



#### Context

- study several approaches
  - \* prosodic classifier: uses intonation
  - \* linguistic classifier: uses the linguistic information
  - \* combined classifier: uses both types of information

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## Prosodic features (#10)

- generally, a question has a final rising pitch
- we compute 10 prosodic features that take into account
  - \* the duration
  - \* the energy
  - \* the pitch

of the last prosodic group of the sentence

## Prosodic features (#10)

#### **Features vector**

class	{0=statement; 1=question}		
	VNDurNorm	= the duration of the last syllable (normalized)	
S <sub>S</sub>	VNLogENorm	= the logarithm of the energy of the last syllable (normalized)	
Prosodic Features	VNF0Delta	$= \mbox{ the F0 difference between the last syllable and the first} \\ \mbox{ syllable}$	
.i	VNF0Slope	= the F0 slope on the last syllable	
pos	VNF0SlopeT2	= VNF0Slope * VNDurNorm <sup>2</sup>	
Pro	globalSlopeSlope	= the F0 slope on the longest ending F0 slope	
	globalSlopeLength	= the length of the longest ending F0 slope	
	globalSlopeDelta	<ul> <li>the F0 difference between the beginning and the end of the longest ending F0 slope</li> </ul>	
	globalSlopeSlopeT2	= globalSlopeSlope * globalSlopeLength <sup>2</sup>	
	lastF0Level	= the last F0 level (normalized by speaker)	

## Linguistic features (#3)

- iP: the interrogative patterns
  - ightarrow indicate the presence or absence of an interrogative pattern in a phrase
  - \* quel
  - \* quelle
  - \* quels
  - \* quellles
  - \* comment
  - \* combien

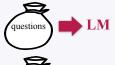
- \* pourquoi
- \* est ce que
- \* est ce qu'
- \* qu' est ce
- \* qu' est ce que
- \* qu' est ce qu'

## Linguistic features (#3)

- the probability of the sentence being a question
  - \* with respect to two reference language models

$$LLR(sentence) = Log\left(\frac{P(sentence|LM-question)}{P(sentence|LM-statement)}\right)$$

- \* LLR  $\geq$  0  $\rightarrow$  likely to be a question
- $\ast$  LLR < 0  $\rightarrow$  likely to be a statement





| we apply the lexical language models on the sequence of words

| synLLR | we apply the syntactic language models on the sequence of POS tags

## Combined linguistic-prosodic features (3L-10P)

#### **Features vector**

class	{0=statement; 1=question}		
	lexLLR	= the lexical log-likelihood ratio	
31	synLLR	= the syntactic log-likelihood ratio	
	iP	= presence or absence of interrogative pattern	
	VNDurNorm	= the duration of the last syllable (normalized)	
	VNLogENorm	= the logarithm of the energy of the last syllable (normalized)	
	VNF0Delta	= the F0 difference between the last syllable and the first syllable	
10P	VNF0Slope	= the F0 slope on the last syllable	
	VNF0SlopeT2	= VNF0Slope * VNDurNorm <sup>2</sup>	
	globalSlopeSlope	= the F0 slope on the longest ending F0 slope	
	globalSlopeLength	= the length of the longest ending F0 slope	
	globalSlopeDelta	= the F0 difference between the beginning and the end of the longest ending F0 slope	
	globalSlopeSlopeT2	= globalSlopeSlope * globalSlopeLength <sup>2</sup>	
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## Data for LM training

#### Textual corpus GigaWord

- extraction of statements : sentences ending with a '.' [#16M]
- extraction of questions : sentences ending with a '?' [#89K]

#### word sequences

question	à quel moment le raid a décidé d'intervenir?
statement	nous sommes ensemble pour 60 minutes.



the lexical language models of questions and statements

#### part-of-speech (POS) sequence

question	PRP PRO: REL NOM DET: ART NOM VER: pres VER: pper PRP VER: infi
statement	PRO: PER VER: pres ADV PRP NUM NOM



the syntactic language models of questions and statements

## Data for training and evaluating the classifiers

- Audio corpus: Ester, Etape, Epac
  - \* training set : 300h of speech (manually transcribed)
  - evaluation set : 22h of speech (manually transcribed)
  - Ester&Epac: French broadcast news, collected from radio channels (prepared speech, plus interviews)
  - Etape: debates collected from various French radio and TV channels (spontaneous speech)
- Data sets of questions and statements
  - → sentences ending with a '?', respectively with a '.'

	#questions	#affirmations
training	10.0K	10.0K
evaluation	0.8K	7.0K

## Question / Statement classification

#### 4 classifiers

- \* LR (logistic regression)
- \* J48 (decision tree)
- \* JRip (decision rules)
- \* MLP (multi-layer perceptron)

#### evaluate classifier using

- \* features extracted from manual transcriptions
  - $\rightarrow$  ideal conditions 0% word error rate
- \* features extracted from automatic transcriptions
  - $\rightarrow$  real conditions 26% word error rate

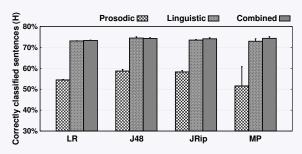
#### performance

$$\frac{1}{H} = \frac{1}{2} * \left( \frac{1}{\text{ccQuestions}} + \frac{1}{\text{ccStatements}} \right)$$

 ${\it ccQuestions} = {\it percentage} \ {\it of} \ {\it correctly} \ {\it classified} \ {\it questions}$   ${\it ccStatements} = {\it percentage} \ {\it of} \ {\it correctly} \ {\it classified} \ {\it statements}$ 

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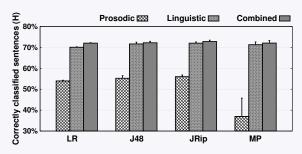
## Results on manual transcriptions



Analysis of the average classifier's performance when applied on manual transcriptions

- $\Rightarrow$  the linguistic classifiers outperform the prosodic classifiers
- $\Rightarrow$  the combination of linguistic and prosodic features does not provide any significant improvement on manual transcripts

## Results on automatic transcriptions



Analysis of the average classifier's performance when applied on automatic transcriptions

- ⇒ the linguistic classifiers outperform the prosodic classifiers
- $\Rightarrow$  3% performance loss between the manual and the automatic transcriptions
- $\Rightarrow$  the combination of linguistic and prosodic features provides a slight improvement on automatic transcription

## Best results on manual and automatic transcriptions

 Confusion matrix between questions and statements obtained on manual transcriptions (MLP, H=75.05%)

	number	classified as	classified as
		question	statement
question	831	603	228
statement	7005	1559	5446

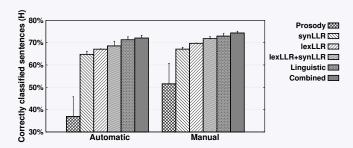
ccQuestions=72.56% ccStatements=77.74%

 Confusion matrix between questions and statements obtained on automatic transcriptions (MLP, H=73.50%)

	number	classified as question	classified as statement
question	831	611	220
statement	7005	1863	5142

ccQuestions=73.60% ccStatements=73.41%

## Impact of different feature combinations



Analysis of the average performance obtained with the MLP classifier when using different feature combinations on automatic and manual transcriptions

- ⇒ the most important linguistic feature is the lexical log-likelihood ratio (lexLLR)
- $\Rightarrow$  the best results are obtained when combining all features

Assess the performance loss when the sentence boundaries are not perfect

- → change the predefined sentence boundaries
  - \* by shifting each boundary (left and right) with a random value of  $\{-300, -200, -100, +100, +200, +300\}$ ms
  - \* by shifting each boundary (left and right) with a random value of  $\{-1000, -800, -600, -400, -200, +200, +400, +600, +800, +1000\}$ ms
  - \* by finding the longest silence-enclosed sentence

#### Reference sentence:

"que fallait -il faire" [947090,948370]

946230	946290	++micro++	60 [ms]
946300	946350	à	50 [ms]
946360	946660	travers	300 [ms]
946670	946760	le	90 [ms]
946770	947020	monde	250 [ms]
947030	947160	<sil></sil>	130 [ms]
947230	947450	++resp++	220 [ms]
947460	947650	que	190 [ms]
947660	947920	fallait	260 [ms]
947930	948080	-il	150 [ms]
948090	948350	faire	260 [ms]
948360	948390	eh	30 [ms]
948400	948530	bien	130 [ms]
948540	948670	il	130 [ms]
948680	948870	fallait	190 [ms]
948880	949310	choisir	430 [ms]
949320	949400	++rire++	80 [ms]

Modified borders  $\pm$  300ms: [+200,+300ms]

"que fallait -il faire eh bien il" [947290,948670]

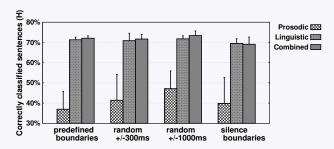
946230	946290	++micro++	60 [ms]
946300	946350	à	50 [ms]
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948540	948670	il	130 [ms]
948680	948870	fallait	190 [ms]
948880	949310	choisir	430 [ms]
949320	949400	++rire++	80 [ms]

Modified borders  $\pm$  1000ms: [-400ms,-600ms] "le monde que fallait" [946690,947770]

946230	946290	++micro++	60 [ms]
946300	946350	à	50 [ms]
946360	946660	travers	300 [ms]
946670	946760	le	90 [ms]
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948880	949310	choisir	430 [ms]
949320	949400	++rire++	80 [ms]

**Modified borders:** the longest silence-enclosed sentence "que fallait -il faire eh bien il fallait choisir" [947460,949310]

946230	946290	micro	60 [ms]
		++micro++	
946300	946350	à	50 [ms]
946360	946660	travers	300 [ms]
946670	946760	le	90 [ms]
946770	947020	monde	250 [ms]
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948880	949310	choisir	430 [ms]
949320	949400	++rire++	80 [ms]



Analysis of the average performance obtained with the MLP classifier on automatic transcriptions when modifying the predefined boundaries

 $\Rightarrow$  even if an automatic segmentation module wrongly assigns the sentence boundaries, our classifier still manages to correctly classify the question/statements entries between 69% and 72%

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#### Conclusions and future work

#### Conclusions

- \* the prosodic classifier gives poor classification results
- the linguistic classifier provides by far better results
   (72% on ASR transcripts, 74% on manual transcripts)
- the combination of prosodic and linguistic features provides a slight improvement when applied on automatic transcriptions
- \* all 13 features are useful in detecting questions and statements
- \* even if an automatic segmentation module wrongly assigns the sentence boundaries, our classifier still manages to correctly classify the question/statements entries between 69% and 72%

#### Investigate further

\* the use of confidence measures inside the classifier

# Thank you for your attention!