

ABSTRACT

Some people can mix two languages within the same sentence: this is known as intra-sentential code-switching. The majority of computational models on language comprehension are dedicated to one language. Some bilingual models have also been developed [3][8], but very few have explored the code-switching case.

We collected data from human subjects that were required to mix pairs of given sentences in French and English. Truly bilingual subjects produced more switches within the same sentence. The corpus obtained have some very complex mixed sentences: there can be until eleven language switches within the same sentence.

We then trained **ResPars**, a **Reservoir-based sentence Parsing model**, with the collected corpus. This Recurrent Neural Network model processes sentences incrementally, word by word, and outputs the sentence meaning (i.e. thematic roles). Surprisingly the model is able to learn and generalize on the mixed corpus with performances nearly as good as the unmixed French-English corpus.

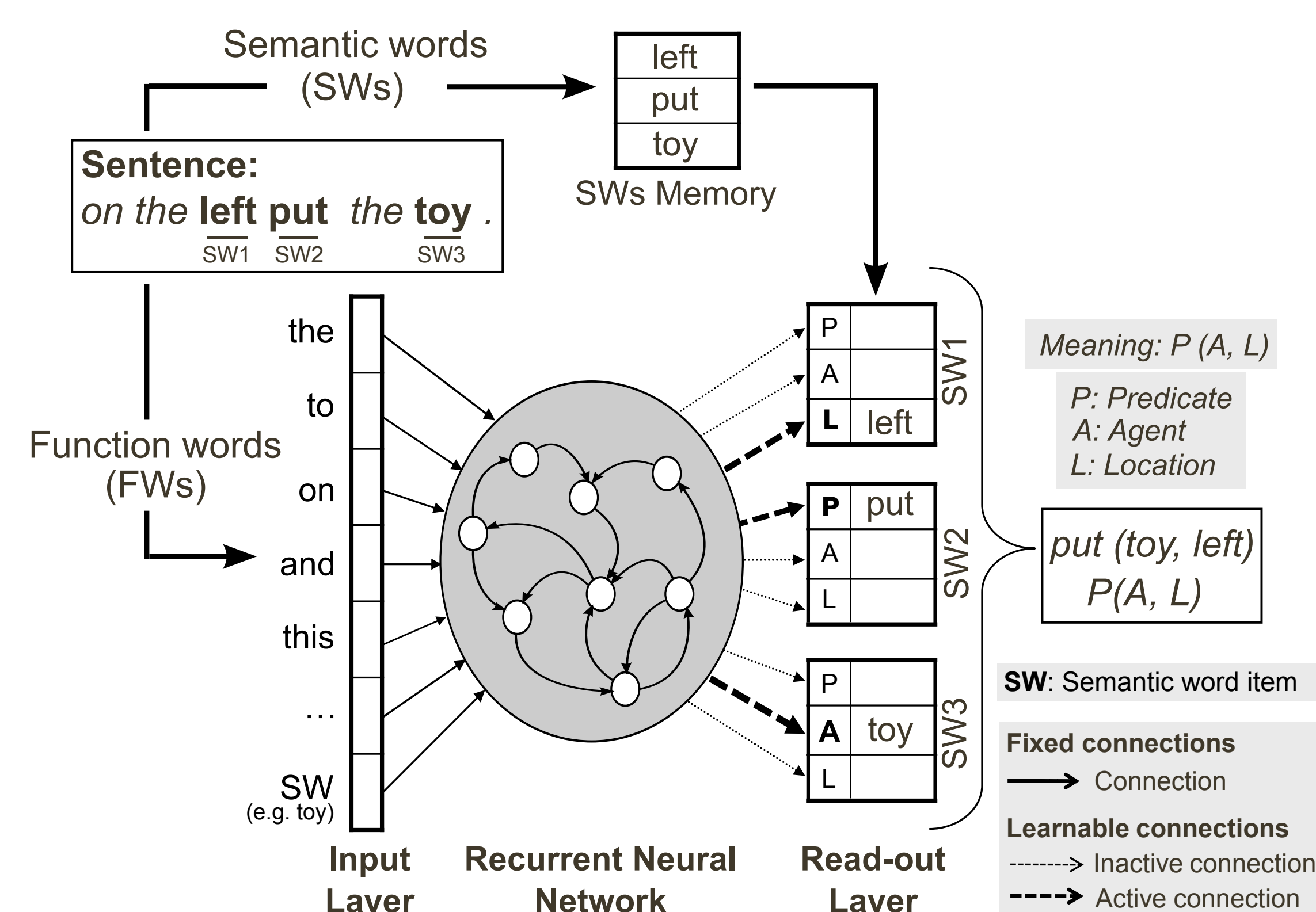
MOTIVATION

You are in a bar in Montreal, you just went out of the CogSci conference. While you are waiting for your beer, you notice that your neighbours that were talking in French just switched to English for a couple of sentences, and then switched back to French. Your beer is served, but intrigued you stay a bit to wait and see. You notice that they often not only borrow some words from one language to another, but they also make part of sentences in French and part in English. You wonder how their can do such a thing so naturally.

Bilingual experimental studies are particularly interesting because they could provide more general memory mechanisms in general compared to mono-lingual studies, for example language lexical access and lexical selection [1].

The same idea also works for bilingual computational models: making a model work for several languages prevents from overfitting and enable to draw more generic conclusions. In other words, adding more languages, and thus more constraints on a model, helps to tackle more general mechanisms, instead of implementing mechanisms that could be specific to one language.

RESPARS NEURAL MODEL



The command “On the left put the toy” given as input to the ResPars model produces the meaning “put(toy, left)” as output which could then be executed by the robot. For each semantic (i.e. content) word the model provides the role in the output (i.e. read-out) layer. Only connections from the Recurrent Neural Network to the outputs are trained; input and recurrent connections are kept random. In *Construction Condition* each semantic word is replaced by a SW marker. In *Sentence Condition* all words are processed equally.

METHODS

Echo State Networks

Update equation of the reservoir (recurrent layer) and the readout [5]:

$$\mathbf{x}(t+1) = (1 - \alpha)\mathbf{x}(t) + \alpha f(\mathbf{W}^{\text{in}}\mathbf{u}(t+1) + \mathbf{W}\mathbf{x}(t)) \quad (1)$$

$$\mathbf{y}(t) = \mathbf{W}^{\text{out}}\mathbf{x}(t) \quad (2)$$

Matrices \mathbf{W}^{in} and \mathbf{W} are randomly generated.

Training of the output weights with ridge regression:

$$\mathbf{W}^{\text{out}} = \mathbf{Y}^d \mathbf{X}^T (\mathbf{X} \mathbf{X}^T + \beta \mathbf{I})^{-1} \quad (3)$$

Model parameters and simulations

We used the same parameter as those described in [10] using 500 units inside the reservoir. Ridge parameter (for regularization) is the only parameter that what optimized depending on the condition. All results are expressed as an error rate averaged over a 10-fold cross validation and averaged on 50 different reservoir instances (i.e. independent simulations). The error rate corresponds to one minus the average number of time a test sentence is fully recognized (i.e. all the roles for each words are correct).

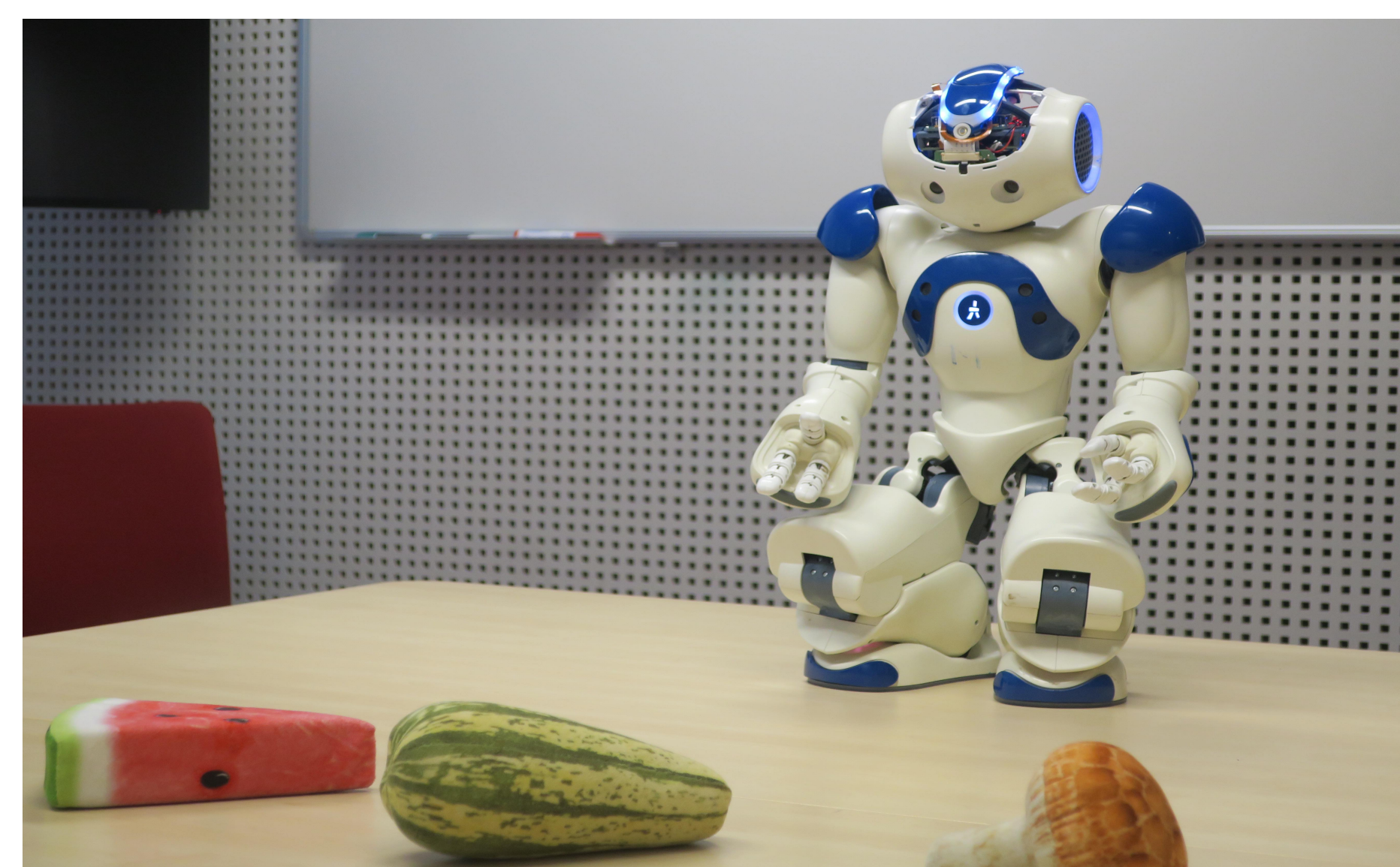
Subject Data Collection

We asked our ten subject with good levels of French and English (two of them were true bilingual) to produced mixed sentences in French-English. Each subject had to mix 38 sentences in French paired with the 38 English sentences with the same meaning (original corpus is from [3]). We constrained them to produce half of the sentences beginning with a French word and half beginning with an English word.

TYPE	SENTENCE EXAMPLE
1	touch the circle after having pushed the cross to the left
1	put the cross on the left side and after grasp the circle
2	move the circle to the left then the cross to the middle
3	put first the triangle on the middle and after on the left
4	push the triangle and <i>the circle on the middle</i>
5	hit twice the blue circle
5	grasp the circle two times
6	put the cross to the right and do a u-turn
7	put both the circle and the cross to the right

English original corpus [3]: Different type of sentences showing the complexity to generalize
1. Sequence of actions 2. Implicit reference to verb 3. Implicit reference to verb and object 4. Crossed reference 5. Repeated action 6. Unlikely action 7. Particular Function Word (FW)

APPLICATION EXAMPLE



Example of Human-Robot Interaction experiment with the Nao robot that includes the ResPars model [9].

RESULTS

Mixed Corpus: Sentence examples produced by subjects

Segments	Chunks	Code-switching sentences produced by subjects
2	2	Hit the triangle puis touche la croix.
2	2	Pointe la croix rouge and point the circle.
6	0	Déplace the cross à ma gauche and then attrape the circle.
3	1	Déplace la croix rouge to the left puis touche le rond bleu.
11	0	Put la cross à right puis push la cross to la right.
3	0	Point la croix twice.
3	0	Touch le triangle after having pointed at it.

We define a segment as a contiguous sequence of words in one language and a chunk as a contiguous sequence of words expressing one full action in only one language.

Model generalization performances

Corpus	Condition	Error (at least 1 role not recognized)
French + English	Sentence	0.208 (0.012)
	Construction	0.165 (0.009)
Mixed	Sentence	0.231 (0.015)
	Construction	0.225 (0.013)
French + English + Mixed	Sentence	0.178 (0.008)
	Construction	0.168 (0.010)

DISCUSSION

Interestingly, learning code-switched sentences do not seem much more difficult than original sentences for the ResPars model. It is able to learn and generalize on the Mixed corpus with performances nearly as good as the original French + English corpus for the sentence condition: performance obtained are about 79.2% for French + English corpus and 76.9% for Mixed corpus. Construction condition is more favorable for French + English corpus though.

Overall performances are slightly increasing when training the model on the Full corpus (French + English + Mixed) rather than the French + English corpus alone: generalization performance obtained are 82.2% (Full) and 79.2% (French + English) for the sentence condition. Performances on the construction condition are equivalent: 83.2% (Full) and 83.5% (French + English). This result is surprising given that Mixed corpus has a lot of variability in the segmentations performed by subjects, and chunks are not frequently used.

In fact, corpus analyses revealed that bilingual subjects tend to produce more segmented sentences (i.e. more switches within a sentence) and performed the task faster (with less cognitive cost) compared to non-bilingual subjects, which tend to produce more chunks (i.e. a complete action described in one language).

We did not observe an effect on the segmentation whether the switch direction was from dominant-to-weak or from weaker-to-dominant language. This difference compared to the results of [6] may be due to the fact that our subjects had to produce sentences only by picking words from written sentences that were given. On the contrary, the study of [6] was based on subjects reading sentences and thus subjects did not have access to the both French and English versions of the sentences.

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