

Assessing the import of morphology in gender assignment: A computational study of French

Nazanin Shafiabadi Nina Nusbaumer Olivier Bonami

Université Paris Cité, LLF, CNRS

LLcD 2024

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991).

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)
 - ▶ **phonological:** [paj]_F (straw), [aksǽ]_M (accent)

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)
 - ▶ **phonological:** [paj]_F (straw), [aksǎ]_M (accent)
 - ▶ **morphological:** *chanteuse*_F (singerF), *chanteur*_M (singerM)

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)
 - ▶ **phonological:** [paj]_F (straw), [aksǎ]_M (accent)
 - ▶ **morphological:** *chanteuse*_F (singerF), *chanteur*_M (singerM)
- ▶ **Entanglement** of these predictors:

Is the gender of the noun *chanteuse*_F predictable because of its semantic properties or because of the suffix *-euse*?

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)
 - ▶ **phonological:** [paj]_F (straw), [aksǎ]_M (accent)
 - ▶ **morphological:** *chanteuse*_F (singer_F), *chanteur*_M (singer_M)
- ▶ **Entanglement** of these predictors:
Is the gender of the noun *chanteuse*_F predictable because of its semantic properties or because of the suffix *-euse*?
- ▶ Predicting gender in French:
 - ▶ 2-gender system: **FEM**, **MASC**
 - ▶ 1/3 of nouns with a unique gender end in a derivational suffix (Bonami et al., 2019)
 - ▶ The relevant suffixes are for the most part compatible with only one gender (Bonami & Boyé, 2019)

Gender Assignment

- ▶ Far from arbitrary (Corbett, 1991). Some predictors:
 - ▶ **semantic:** *femme*_F (woman), *homme*_M (man)
 - ▶ **phonological:** [paj]_F (straw), [aksǎ]_M (accent)
 - ▶ **morphological:** *chanteuse*_F (singer_F), *chanteur*_M (singer_M)
- ▶ **Entanglement** of these predictors:
Is the gender of the noun *chanteuse*_F predictable because of its semantic properties or because of the suffix *-euse*?
- ▶ Predicting gender in French:
 - ▶ 2-gender system: **FEM**, **MASC**
 - ▶ 1/3 of nouns with a unique gender end in a derivational suffix (Bonami et al., 2019)
 - ▶ The relevant suffixes are for the most part compatible with only one gender (Bonami & Boyé, 2019)
- ▶ **Is gender prediction based on morphology or phonology?**

Previous Attempts

- ▶ Since the 2000s, various attempts to use machine learning techniques to study gender assignment.
- ▶ General idea:
 - ▶ Set up a (computational) classifier predicting gender from a set of other features.
 - ▶ Train the classifier on part of the data.
 - ▶ The accuracy of the classifier on unseen data reflects how hard it is to predict gender from that set of features.
- ▶ Some examples:

Study	Language	Genders	Datapoints	Method
Sokolik & Smith (1992)	French	2	600	Simple NN
Eddington (2002)	Spanish	2	2,416	Skousen's AML
Matthews (2005)	French	2	1,590	Perceptron / AML
Plaster et al. (2013)	Tsez	4	3,500	Decision Trees
Bonami et al. (2019)	French	2	3,683	Multilayer perceptron
Fedden et al. (in press)	German	3	30,576	Boosting Trees

Our Study

- ▶ Focus on predicting the gender of French nouns from their **orthographic** or **phonemic** form.
- ▶ Investigation of how the presence of suffixes influences prediction **in the absence of explicit morphological boundaries**.
- ▶ Primary data source: ***Flexique*** (Bonami et al., 2014):
 - ▶ French inflectional lexicon
 - ▶ Using only nouns (total: 29,411)

Gender	Distribution	
MASC	56%	17,192
FEM	39%	12,219
Both	5%	1,593

- ▶ For a subset of the nouns, morphological annotation from ***Echantinom*** (Bonami & Tribout, 2021) is available, and will be used for evaluation.

Data Preparation

- ▶ **Dataset:** French nouns with gender labels
 - ▶ **Training set:** 80% (random split) of *Flexique* (F), excluding all nouns that appear in *Echantinom* (E) and nouns with both genders (b)
 - ▶ **Validation set:** The remaining 20% of *Flexique*
 - ▶ **Testing set:** *Echantinom*, excluding all nouns with both genders

Set	Noun Count	Composition
Training	19,904	$(F - E - b) \times 80\%$
Validation	4,976	$(F - E - b) \times 20\%$
Test	4,532	$(E - b)$

- ▶ **Preprocessing:** Word forms reversed and split into characters

Model Selection

- ▶ **Model:** GenderLSTM (LSTM architecture)
- ▶ **Reason:**
 - ▶ Effective for handling sequential data
 - ▶ Generates a prediction after each character is processed
 - ▶ Relatively simple architecture

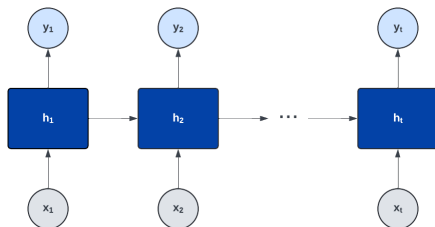


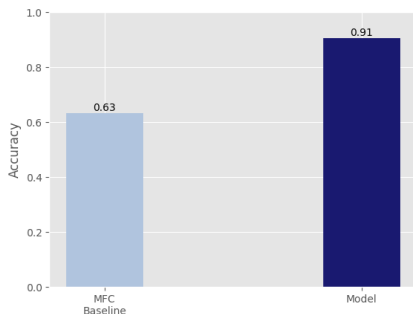
Figure: Unidirectional LSTM Architecture

Model Architecture

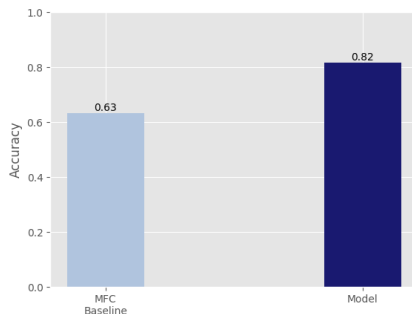
- ▶ **Embedding Layer:** Converts characters into vectors
- ▶ **LSTM Layer:** Processes character sequences
- ▶ **Linear Layer:** Transforms LSTM outputs into logits for class predictions
- ▶ **Output Layer:** Outputs probability distributions over the different genders for each character and the final hidden state for loss computation

Comparison with MFC Baseline

- ▶ The chosen architecture is successful in capturing the gender patterns
- ▶ Gender is more predictable from the **orthographic** form of the nouns than from the **phonemic** form



(a) **Orthographic** Model



(b) **Phonemic** Model

Comparing the Models' Performances

- ▶ Analyzed the predictions for **4,532** lemmas (Test set)

Comparing the Models' Performances

- Analyzed the predictions for **4,532** lemmas (Test set)

	FEM	MASC
Correct	87% (1438)	93% (2664)
False	13% (220)	7% (209)

Orthographic model accuracy

Comparing the Models' Performances

- Analyzed the predictions for **4,532** lemmas (Test set)

	FEM	MASC
Correct	87% (1438)	93% (2664)
False	13% (220)	7% (209)

Orthographic model accuracy

	FEM	MASC
Correct	70% (1167)	89% (2549)
False	30% (492)	11% (323)

Phonemic model accuracy

Comparing the Models' Performances

- Analyzed the predictions for **4,532** lemmas (Test set)

	FEM	MASC
Correct	87% (1438)	93% (2664)
False	13% (220)	7% (209)

Orthographic model accuracy

	FEM	MASC
Correct	70% (1167)	89% (2549)
False	30% (492)	11% (323)

Phonemic model accuracy

- They agree for **84%** of the lemmas.

What are frequent errors common to both models?

- ▶ Errors common to the **orthographic** and **phonemic** models.
- ▶ Testing using *Echantinom*'s morphological annotations.
- ▶ Hypothesis:
 - ▶ The model learns from statistical associations between endings and gender.
 - ▶ These associations are mostly due to the presence of gender assigning suffixes.
 - ▶ Errors are driven by words that go against these associations.

What are frequent errors common to both models?

- ▶ Errors common to the **orthographic** and **phonemic** models.
- ▶ Testing using *Echantinom*'s morphological annotations.
- ▶ Hypothesis:
 - ▶ The model learns from statistical associations between endings and gender.
 - ▶ These associations are mostly due to the presence of gender assigning suffixes.
 - ▶ Errors are driven by words that go against these associations.

Process	Distribution in the dataset	Proportion among errors	Examples
Simplex	43% (1,943)	66% (159)	<i>gruyère, crypte</i>
Suffix	37% (1,701)	11% (27)	<i>capitaine, fureur, minceur</i>
Nonconcat	2% (96)	7% (17)	<i>info, mayo, berlingue</i>
Conversion	10% (473)	7% (17)	<i>velouté, uniforme, hongre?</i>
Polylexical	5% (240)	6% (15)	<i>serre-tête, bain-marie, croquemi-taine</i>
Prefix	2% (81)	3% (7)	<i>mi-juillet, antigène, demi-frère</i>

Some Common Simplicia Endings

Ending	Distribution in the dataset	Distribution among errors	Examples
-age	 (895)	 (3)	<i>cage, rage, nage</i>
-ère	 (469)	 (3)	<i>frère, gruyère, cimetière</i>
-ion	 (1791)	 (5)	<i>scion, bastion, centurion</i>
-eur	 (1552)	 (4)	<i>fleur, rumeur, couleur</i>
-ule	 (155)	 (3)	M: <i>bidule</i> ; F: <i>capsule, mandibule</i>
-ane	 (113)	 (4)	M: <i>crane, arcane</i> , F: <i>chicane</i>
-che	 (255)	 (3)	<i>prêche, guinche, panache</i>
-sse	 (284)	 (3)	<i>cause, bidasse, carrosse</i>
-oge	 (9)	 (2)	<i>toge, loge</i>

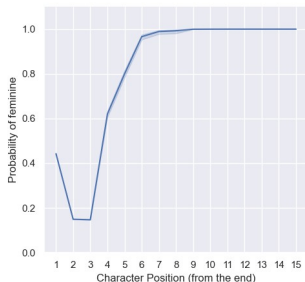
 FEM

 MASC

Observations I

- Words with the same suffix have similar curves

(a) Orthographic Model



(b) Phonemic Model

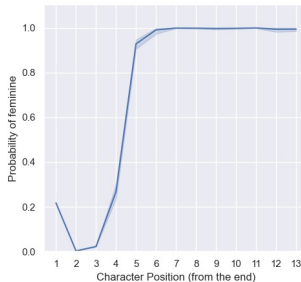


Figure: Average probability distribution of words with suffix "ion" (162 samples)

Observations II

- There is greater variation within runs for the same word than runs for different words sharing the same suffix

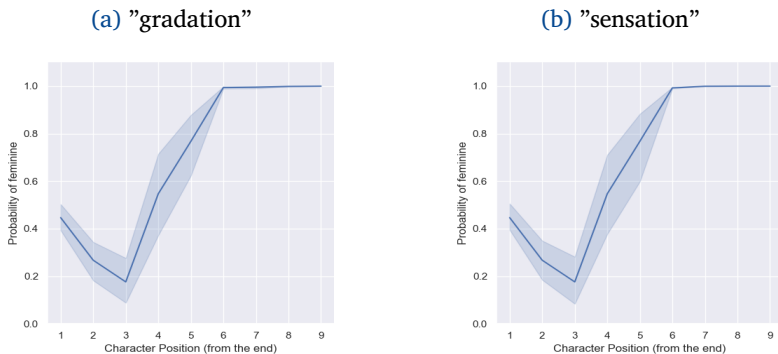
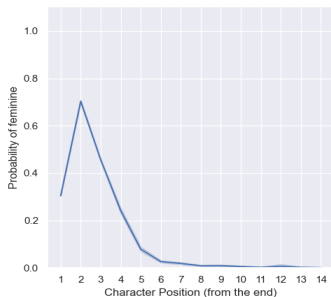


Figure: Comparison of the probability distribution of two words ending in "ion" over 10 runs.

Interesting Cases I

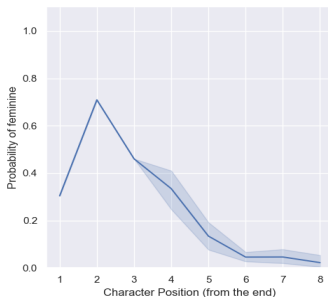
- ▶ Two suffixes with the same form but different genders and meanings have strikingly similar shapes.

(a) "eurM" (193 samples)



e.g. *chauffeur* (driver)

(b) "eurF" (15 samples)

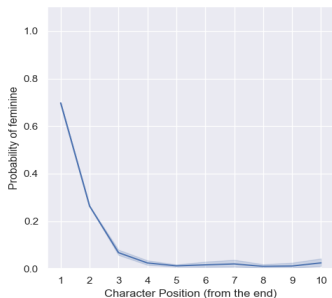


e.g. *fureur* (fury)

Figure: Probability distribution of masculine vs. feminine words ending in "eur".

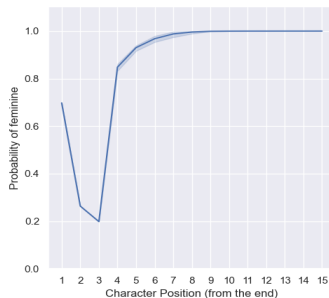
Interesting Cases II

- With similar but not identical suffixes, the shapes diverge.



(a) "on" (72 samples)

e.g. *carton* (cardboard)



(b) "ion" (162 samples)

e.g. *sensation* (sensation)

Figure: Probability distribution of words ending in "on" vs. "ion".

Conclusions

- ▶ An RNN assigns gender correctly with high accuracy based only on the form of the noun (confirming previous work).
- ▶ Error patterns are driven by the presence of endings with strong statistical associations to one gender due to derivational morphology
- ▶ Analysis of the time course of predictions suggests that the model assigns gender based on derivational suffixes
 - ▶ The curves are the same for words with the same suffix
- ▶ Relation to Word and Paradigm?
 - ▶ Other talks in this workshop focus on prediction of one word from another word.
 - ▶ Another important question is prediction of the content of a word from its form (Beniamine 2018).
 - ▶ Here we have looked at how one morphosyntactic feature, gender, can be predicted from the form of nouns.
 - ▶ The same methods could be deployed more generally in the context of paradigms.

Thank You!

References I

- 
- Bonami, Olivier & Gilles Boyé (2019). “Paradigm uniformity and the French gender system.” In: *Perspectives on morphology: Papers in honour of Greville G. Corbett*. Ed. by Matthew Baerman, Oliver Bond, & Andrew Hippisley. Edinburgh: Edinburgh University Press, 171–192 (cit. on pp. 2–8).
- 
- Bonami, Olivier, Gauthier Caron, & Clément Plancq (2014). “Construction d’un lexique flexionnel phonétisé libre du français.” In: *Actes du quatrième Congrès Mondial de Linguistique Française*. Ed. by Franck Neveu et al., pp. 2583–2596 (cit. on p. 10).
- 
- Bonami, Olivier, Matías Guzmán Naranjo, & Delphine Tribout (2019). “The role of morphology in gender assignment in French.” In: *ISMO 2019*. Paris, France (cit. on pp. 2–9).
- 
- Bonami, Olivier & Delphine Tribout (2021). *Echantinom: Morphological Annotations for French*. <https://osf.io/rdxqk/>. Accessed: 2024-07-16 (cit. on p. 10).
- 
- Corbett, Greville G. (1991). *Gender*. Cambridge: Cambridge University Press (cit. on pp. 2–8).
- 
- Eddington, David (2002). “Spanish gender assignment in an analogical framework.” In: *Journal of Quantitative Linguistics* 9, pp. 49–75 (cit. on p. 9).

References II



Fedden, Sebastian, Matías Guzmán Naranjo, & Greville G. Corbett (in press). “Typology meets statistical modeling: the German gender system.” In: *Language* (cit. on p. 9).



Matthews, Clive A. (2005). “French Gender Attribution on the Basis of Similarity: A Comparison Between AM and Connectionist Models.” In: *Journal of Quantitative Linguistics* 12, pp. 262–296 (cit. on p. 9).



Plaster, Keith, Maria Polinsky, & Boris Harizanov (2013). “Noun classes grow on trees: Noun classification in the North-East Caucasus.” In: *Language Typology and Historical Contingency. In honor of Johanna Nichols*. Ed. by Balthasar Bickel et al. Amsterdam: John Benjamins, pp. 153–169 (cit. on p. 9).



Sokolik, M. E. & Michael E. Smith (1992). “Assignment of gender to French nouns in primary and secondary language: a connectionist model.” In: *Second Language Research* 8.1, pp. 39–58 (cit. on p. 9).