

Social gender and derivational morphology:

A distributional study of the gendered import of learned morphology in

French

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- French suffixes *-euse* and *-rice* are clear morphological rivals
 - Feminine agent nouns
 - *danser* 'dance' > *danseuse* 'female dancer'
 - *rédiger* 'write' > *rédactrice* 'female author'
 - Instrument nouns
 - *agrafer* 'staple' > *agrafeuse* 'stapler'
 - *excaver* 'excavate' > *excavatrice* 'excavator'
- Literature has put forth semantic differences with respect to the derived agent nouns (Lenoble-Pinson, 2008; Dawes, 2003, among others)
 - Denotation of low-level professions for *-euse*
 - *serveuse* 'waitress', *entraîneuse* 'barmaid'
 - Denotation of more socially valued positions for *-rice*
 - *directrice* 'female manager', *sénatrice* 'female senator'
- Recent studies show the distributional relevance of this distinction (Wauquier et al., 2020)

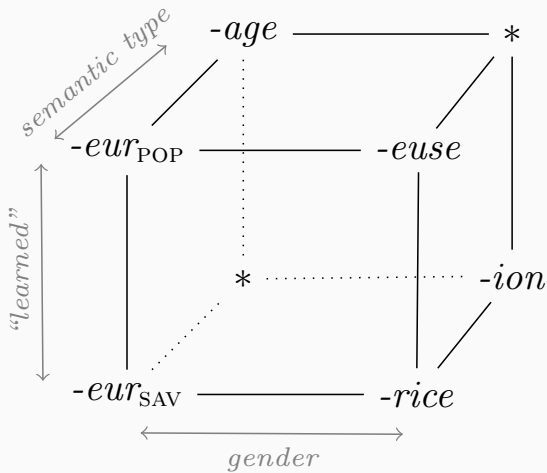
Further differences

- Both suffixes are not strictly identical with respect to their morphological construction
 - *-rice* originates from learned vocabulary (Rainer and Buridant, 2015) similarly to *-ion* and *-if* among others
- This distinction is hardly ever taken into account
 - It's is also at stake for the formation of masculine agent nouns
 - Learned *-eur* attaches to the same stems as *-ion* ('hidden stem', see Bonami et al. 2009) – *fondateur* 'founder', *fondation* 'foundation' from *fonder* 'found'
 - Nonlearned *-eur* attaches to the same nonlearned stems as *-age* – *dresseur* 'trainer', *dressage* 'training' from *dresser* 'train'

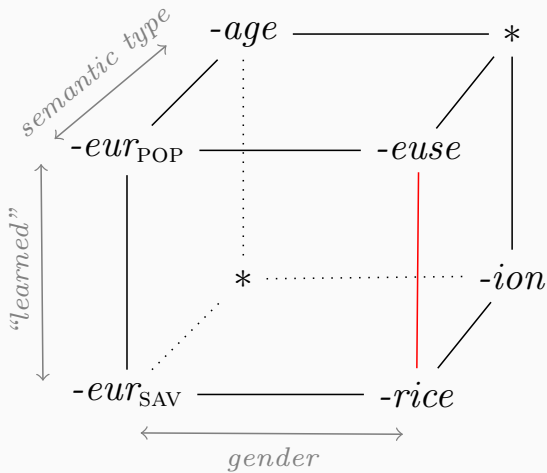
Research question

- To what extent does the semantic distinction between *-euse* and *-rice* follow from their morphological specificity, i.e. their status as learned vs. nonlearned formation?
 - If it does, we expect the differences between learned and nonlearned formations to be parallel for masculine and feminine agent nouns
 - By extension, parallel effects should be found for action nouns in *-ion* and *-age*
- We combine distributional and computational approaches to provide an empirical assessment of these hypotheses.

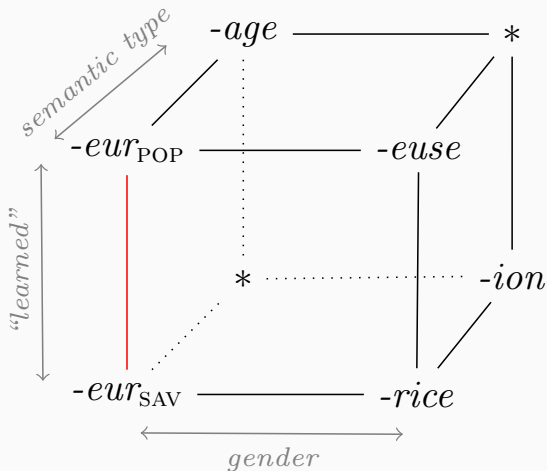
(Non)learned formations in a cube



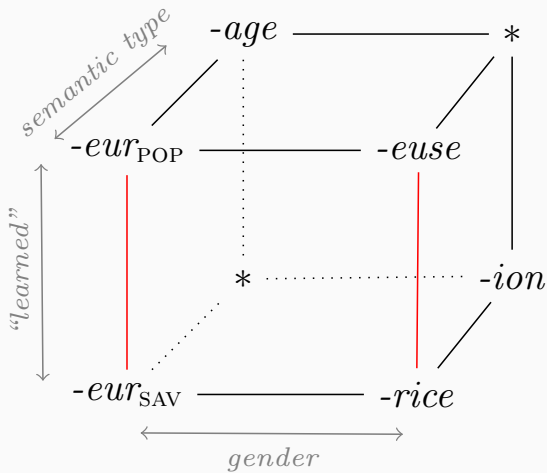
(Non)learned formations in a cube



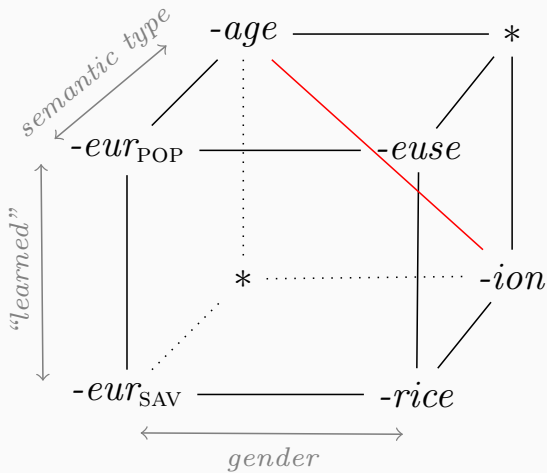
(Non)learned formations in a cube



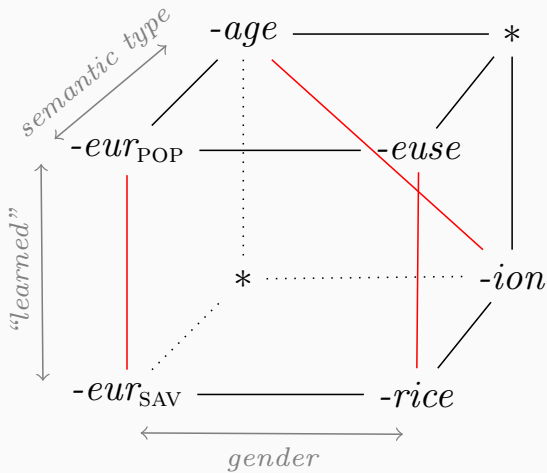
(Non)learned formations in a cube



(Non)learned formations in a cube



(Non)learned formations in a cube



Distributional semantics in a nutshell

- Distributional semantics is grounded in the hypothesis that differences in word meanings are reflected by differences in distribution, i.e. the contexts in which they appear.
- The meaning of words in a given corpus is represented by vectors computed based on their co-occurrences
- The semantic similarity between two words is assessed by the distributional proximity of their vectors on a scale from 0 to 1.

Context \ Target	<i>dog</i>	<i>cat</i>	<i>car</i>
<i>kibble</i>	6	9	1
<i>gas</i>	2	1	8

Table 1: Co-occurrences matrix of 3 targets

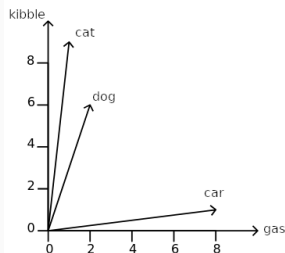
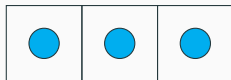
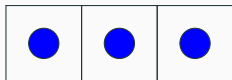


Figure 1: Targets' vectors

- Our vectors are trained
 - with Word2Vec (Mikolov et al., 2013) basic parameters
 - CBOW, 100 dimensions, Negative Sampling, frequency threshold of 5, window of 5
 - On the FrCoW corpus (Schäfer and Bildhauer, 2012; Schäfer, 2015) which was:
 - Lemmatized – e.g. *dînera* → *dîner_ver*
 - Tagged – e.g. *un dîner* → *un_art dîner_nom*
 - Carefully gender-neutralized – e.g. *du* → *de_prep le_art*

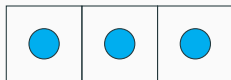
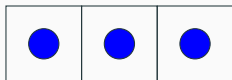
Intrinsic classification task

danseuse



rédatrice

coiffeuse

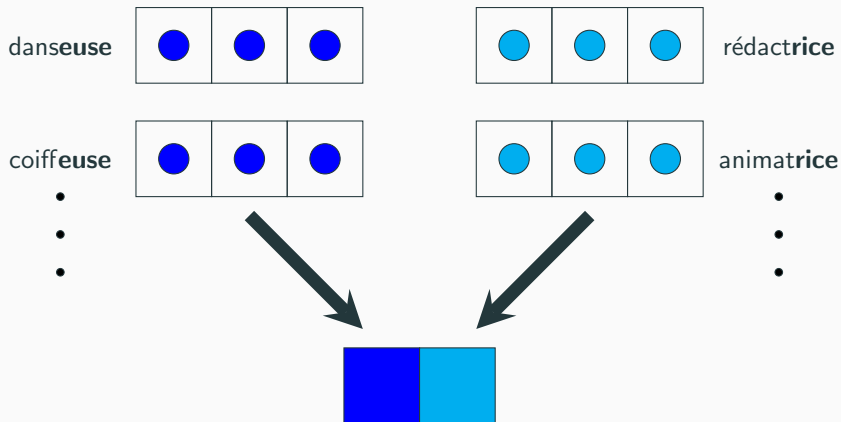


animatrice

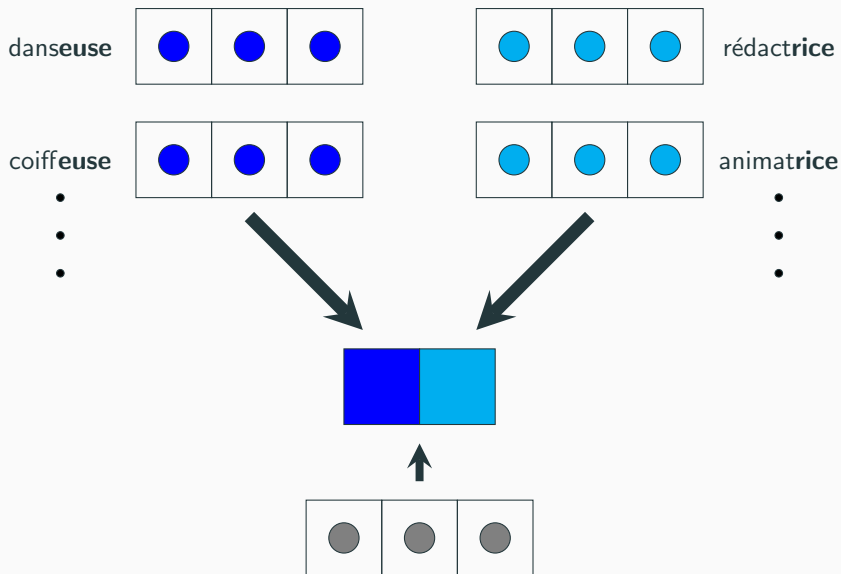
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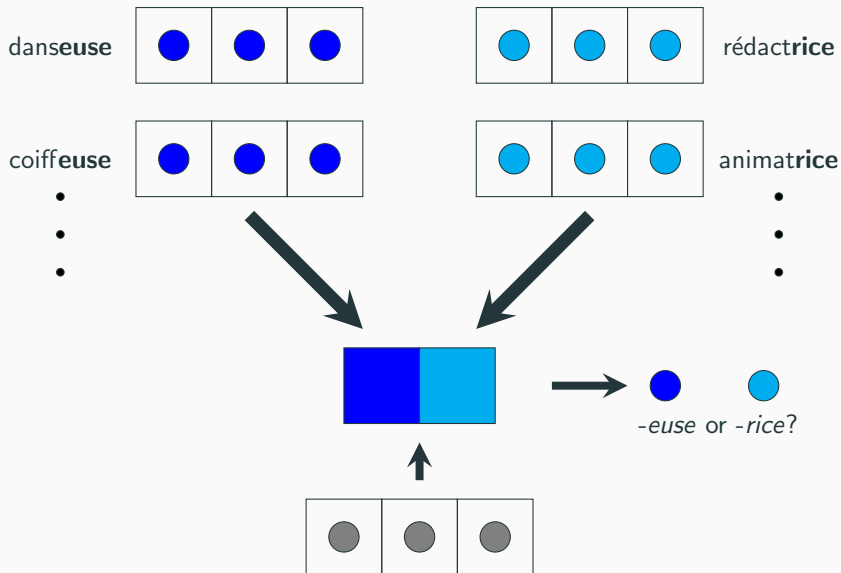
Intrinsic classification task



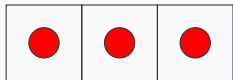
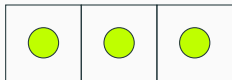
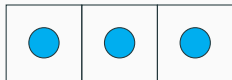
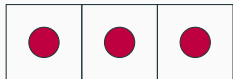
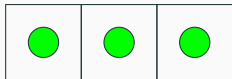
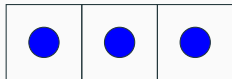
Intrinsic classification task



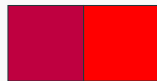
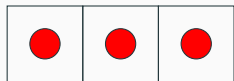
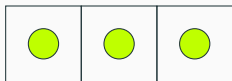
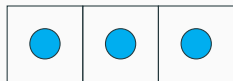
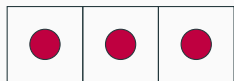
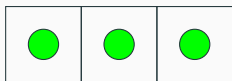
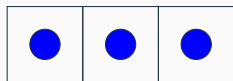
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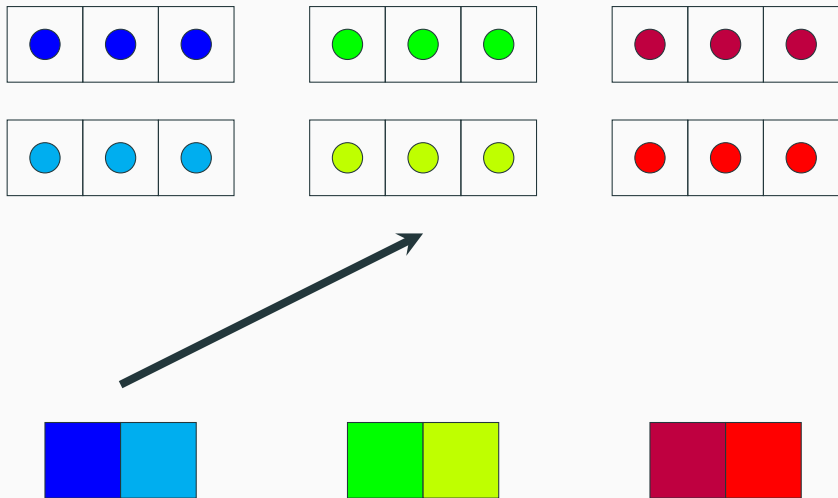
Extrinsic prediction task



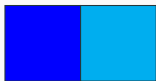
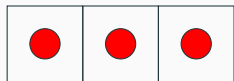
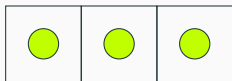
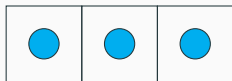
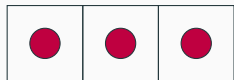
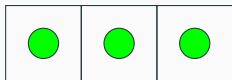
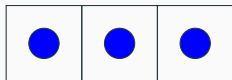
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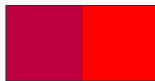
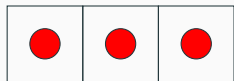
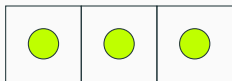
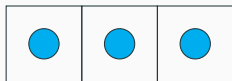
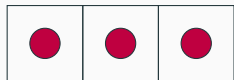
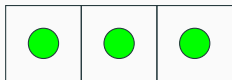
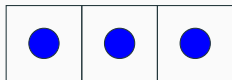
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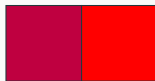
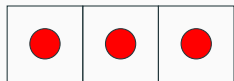
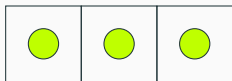
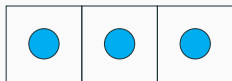
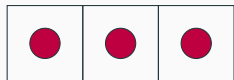
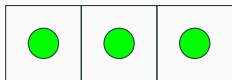
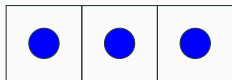
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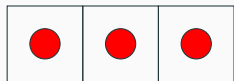
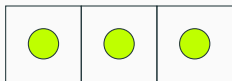
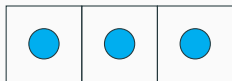
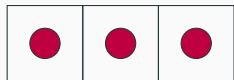
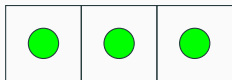
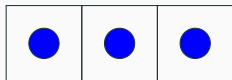
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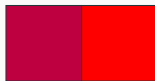
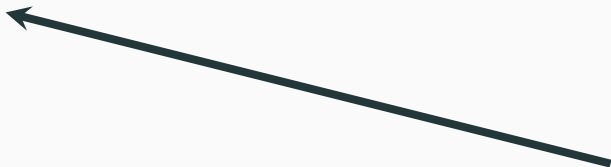
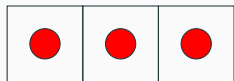
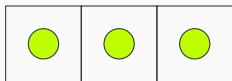
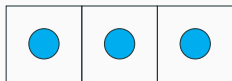
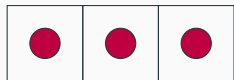
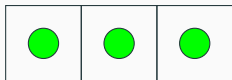
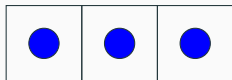
Extrinsic prediction task



Extrinsic prediction task



Extrinsic prediction task



Datasets

- We build three dataset of feminine agent nouns (AGF), masculine agent nouns (AGM) and action nouns (ACT) with the (non)learned alternation
 - All agent nouns were filtered to exclude polysemy
 - Only nouns with a frequency of 50 or more in the FrCow corpus are kept

	Learned	Nonlearned
AGF (<i>rice vs. euse</i>)	158	301
AGM	141	462
ACT (<i>ion vs. age</i>)	750	629

Table 2: Description of our datasets

- We use gradient boosting (Friedman, 2001; Mason et al., 2000) applied to decision trees as our binary classification method
 - 500 estimators, max depth of 2, deviance loss function
- The classifiers are trained on 282 nouns (141 of each suffix)
 - We randomly sub-sample our datasets based on the smallest one
- The performance of the classifiers are evaluated by means of
 - a 10-fold cross-validation for intrinsic predictions
 - a confusion matrix for extrinsic predictions, where suffixes are matched based on their (non)learned status
 - e.g. when the classifier trained on action nouns to predict *-ion* is applied to feminine agent nouns, *-rice* nouns labeled as *-ion* are considered as true positive

- Because we hypothesize that the (non)learned feature is a distinctive but shared feature between all three datasets
 - We expect intrinsic predictions to get good results
 - We expect extrinsic predictions to perform better than the baseline, even similarly to intrinsic predictions

Intrinsic prediction results

- All three classifiers reach relatively high accuracy

	Accuracy	Confidence interval
AGF	80%	75.1 - 84.5
AGM	77%	72 - 81.9
ACT	83%	78.6 - 87.4

Table 3: Performance of intrinsic classifiers

- Despite the small training set, distribution is distinctive enough between learned and nonlearned nouns within each dataset
 - Yet it does not entail that all three datasets vary similarly

Extrinsic prediction results

- Intrinsic and extrinsic predictions lead to very similar accuracy

Training data	Test data		
	AGF	AGM	ACT
AGF	80%	77%	79%
AGM	77%	77%	82%
ACT	76%	79%	83%

Table 4: Accuracy of the three classifiers applied to the three datasets

- The learned vs. nonlearned distinction is equally predicted by all models on all datasets
- This distinction is stable and relevant in the distribution of all three categories of nouns

Qualitative assessment

- It remains to be seen whether this learned vs. nonlearned distinction is link to the observed difference in connotations between *-euse* and *-rice*
 - If so, a difference should be observed for the masculine agent nouns
- We rely on a qualitative assessment of their distribution
 - We build an average representation (*centroid*) for each suffix which we qualify by means of its 100 nearest neighbors

Centroid and neighbors

formatrice

animatrice

inventrice

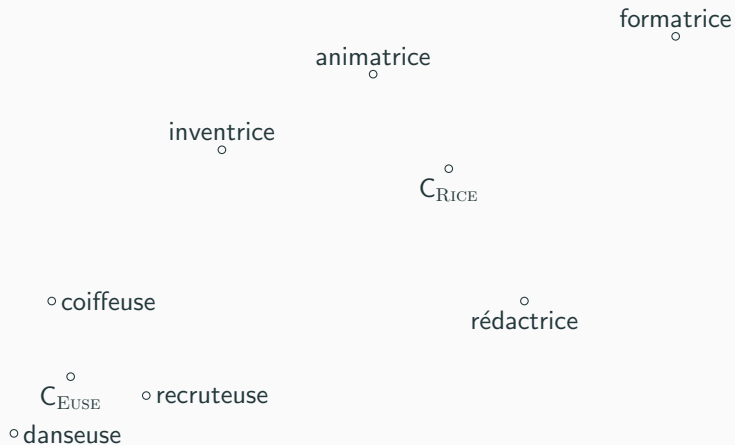
◦ coiffeuse

◦
rédactrice

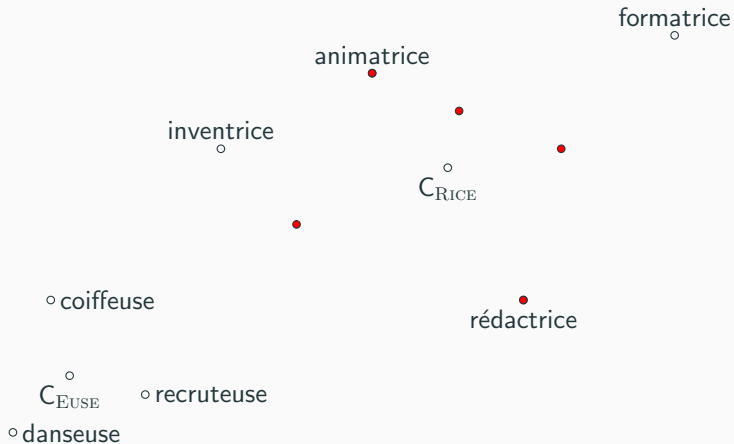
◦ recruteuse

◦ danseuse

Centroid and neighbors



Centroid and neighbors



Semantic properties of the neighbors i

- Learned and nonlearned centroids have distinctive neighborhood
 - AGF centroids only share 8 neighbors out of 100
 - AGM centroids only share 3 neighbors out of 100

Semantic properties of the neighbors i

- Learned and nonlearned centroids have distinctive neighborhood
 - AGF centroids only share 8 neighbors out of 100
 - AGM centroids only share 3 neighbors out of 100
- Learned centroids neighborhoods contain a much lower proportion of negatively valued neighbors than nonlearned centroids neighborhoods
 - Positively valued neighbors
 - *dirigeante* 'female leader', *chirurgienne* 'female surgeon', *avocate* 'female lawyer', *poétesse* 'female poet'
 - *érudit* 'scholar', *académicien* 'academician', *orateur* 'orator', *intellectuel* 'intellectual'
 - Neutral neighbors
 - *camerawoman* 'camerawoman', *formatrice* 'female tutor', *animatrice* 'female presenter'
 - *exécutant* 'subordinate', *journaliste* 'journalist', *comptable* 'accountant', *contributeur* 'contributor'

Semantic properties of the neighbors ii

- The axiological properties of the nonlearned centroids neighbors vary with regard to gender
 - With respect to the feminine agent nouns (AGF), the neighbors involve
 - **Sexuality** – *nymphomane* 'nymphomaniac', *tapineuse* 'prostitute', *catin* 'harlot', *allumeuse* 'tease', *hardeuse* 'pornographic film actress'
 - **Physical characterization** – *laideron* 'plain Jane', *monstresse* 'monstress', *midinette* 'starry-eyed girl'
 - With respect to masculine agent nouns (AGM), they involve
 - **Sexuality** – *dragueur* 'womanizer', *séducteur* 'seducer'
 - **Behavioral characterization** – *tire-au-flanc* 'slacker', *poivrot* 'drunkard', *rustre* 'lout', *paresseux* 'idler'
 - **Criminal activities** – *truand* 'gangster', *voleur* 'thief', *malandrin* 'brigand'

Conclusion i

- We showed that the learned vs. nonlearned distinction instantiated with French feminine and masculine agent nouns and action nouns was distributionally identifiable
 - This feature is discriminative within each category
 - This feature is stable across all three categories
- We highlighted the semantic correlate of the learned vs. nonlearned distinction that varies depending on the morphosemantic type
 - It is instantiated in terms of axiological valence for agent nouns
 - The axiological values differ with respect to the gender and the (non)learned status
 - It implements a contrast between intellectual and technical domains of reference for action nouns (Wauquier et al., 2020)
 - Whether these differences comes particular sociolinguistic circumstances in which learned formations entered the language is yet to be confirmed

- We propose an innovative method to scrutinize the manifestation of a given feature within the lexicon
 - This methodology can be extended to other paradigmatic structures and features

- Institutions

- ANR Project *Demonext* (PI Fiammetta Namer)
- Laboratoire de linguistique formelle (Université de Paris & CNRS)



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Inflectional cube

