Striking out on one's own

Idiosyncratic frequency as a measure of derivation vs inflection

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Outline

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Inflection vs Derivation

- Derivation increasingly recognised as paradigmatic, in a parallel way to inflection
    - See among many others: Marle (1984), Becker (1993), Bochner (1993), Blevins (2001), Stump (2005), Stekauer (2014), Boyé and Schalchli (2016), and Bonami and Strnadová (2019)
- A movement towards a unified, gradient approach based on empirical evidence.

The theory

- While not a dichotomy, **inflection and derivation remain two distinct concepts in theory**

Inflection	Derivation
lire∼lisait	*lire∼lisible*
Outputs realisations of a single lexeme	Outputs independent lexical entries
Same concept	Different concepts

- Can this theoretical difference manifest itself empirically?

A general prediction

- Derivational output is inherently more independent from its base. More variability for members of derivational relationships.
- For example, meaning relationships are more predictable in inflection than derivation (Bonami and Paperno, 2018)

A more specific prediction

- For related reasons, we can expect a **difference in the predictability of word frequency** for inflection and derivation.
- Because **derived lexemes are independent lexical entities**, we expect their frequency to vary independently of their base

Verb	Action noun	Freq. ratio
ouvrer ‘to work’	*ouvrage* ‘work; book’	0.02
cambrioler ‘to rob’	*cambriolage* ‘robbery’	0.34
	median	**17**
arriver ‘to arrive’	*arrivage* ‘delivery’	489
fixer ‘to fasten’	*fixage* ‘fixing’	1927

- In inflection, we do not expect such variability, except where it is semantically motivated (e.g. *eye* is more likely to be found in the plural than *nose*)

The research question

- Is the frequency of the output more predictable for inflection, compared to derivation?
    - Gradient vs dichotomy?
    - What factors are most helpful?

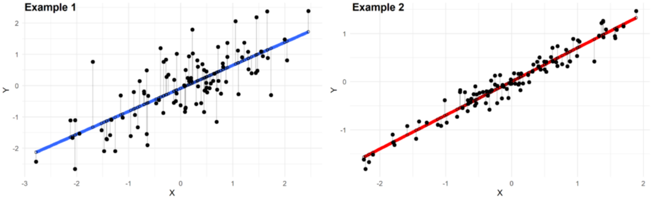
Outline

The methodological plan

How does a given morphological process impact frequency?

- We can train a statistical model for each morphological process to predict the frequency of the output

- We can use goodness of fit measures to compare our different models, and highlight whether some processes are harder to model than others
    - The residual standard error (RSE) of a model quantifies the accuracy of the prediction (low RSE = good prediction)



- …But what predictors should be used?

Frequency

We can use the frequency of a related form for a rough estimate of how frequently the lexeme is used

- We'll use the reference form (verb inf. & noun sg.)

reference form = citation form (of the base)

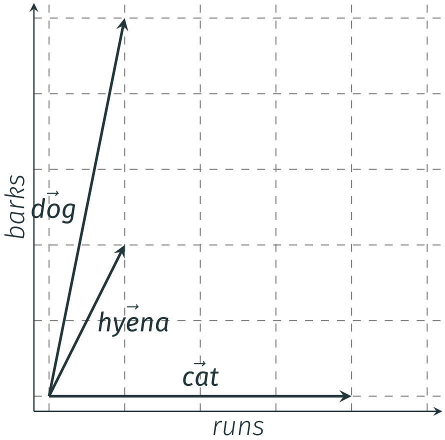
To compute frequencies, we need a large corpus:

- FrCOW 16: 6B tokens, in French, crawled from the web.
- We use the tokenization provided in the XML files.

“Word vectors”

- We want predictors for semantic information

	runs	*barks*
dog	1	5
hyena	1	2
cat	4	0

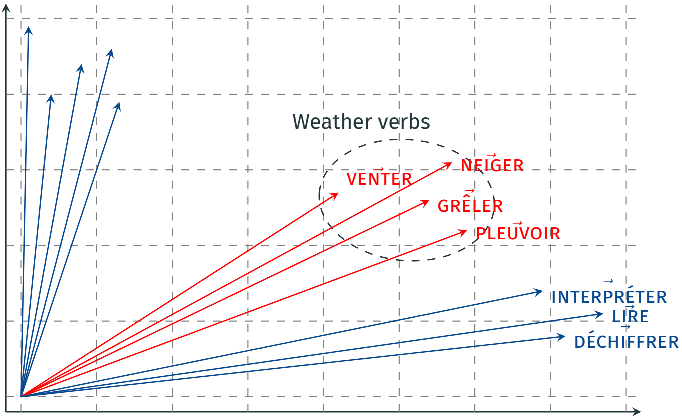


from Baroni, Bernardi, and Zamparelli (2014)

- We can use many different observations, e.g., on words or lexemes
- Frequency is encoded in the length (norm) of a vector

Semantic neighbourhood

- We expect the neighbours of a given word to **share semantic characteristics** with it



Word vectors: to recap

- word vectors reflect lexical semantics
- Regions of the semantic space describe coherent semantic fields (e.g., weather verb vectors are bunched together).

We can use vectors to make **semantically informed predictions.**

- We can use them **directly**: plug in the vector $\vec{w}$ of the word w
  (**Word-level** semantic information)
- We can use them **indirectly**: explore the neighbourhood of $\vec{w}$ which describe the general trend for semantically similar words
  (**Lexeme-level** semantic information)

We'll train **two 100D vector spaces** on FrCOW16 data.

Two many vector components

We want to use vectors as predictors in statistical models

> *"With four parameters I can fit an elephant, and with five I can make him wiggle his trunk."*
>
> John von Neumann

- If we use all 100 vector components, we would have more predictors than distinct responses.
- We can apply dimensionality reduction to solve this issue.

Dimensionality reduction with SVD

Click here for an amazing GIF that we couldn’t be bothered to embed properly!

Outline

The models

- A baseline: $f(output) \sim f(\text{reference form})$

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- $f(output) \sim f$(reference form) + $\overrightarrow{reference\ form}$
  - $f(lirai) \sim f(lire) + \overrightarrow{\text{LIRE}}$
  - why? A way to take base semantics into account
    - Necessary to account for *eye*∼*eyes*, *nose*∼*noses*

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  - average neighbour relative frequency = $\frac{1}{n} \cdot \sum_{i=1}^{n} \frac{neighb\ form_i}{neighb\ ref\ form_i}$
  - $f(lirai) \sim f(lire) + avg(\frac{f(intérpreterai)}{f(intérpreter)} + \frac{f(déchiffrerai)}{f(déchiffrer)} + ...)$
  - why? For processes whose output is heavily dependent on the base, this should provide an accuracy boost.

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    - $f(lirai) \sim f(lire) + \text{avg}(\vec{intérpreterai} + \vec{déchiffrerai} + \ldots)$
    - Neighbours of the base are obtained. The vector of their output is averaged and added as a predictor.
    - why? Same reason for model type 3, but semantics is included more directly.

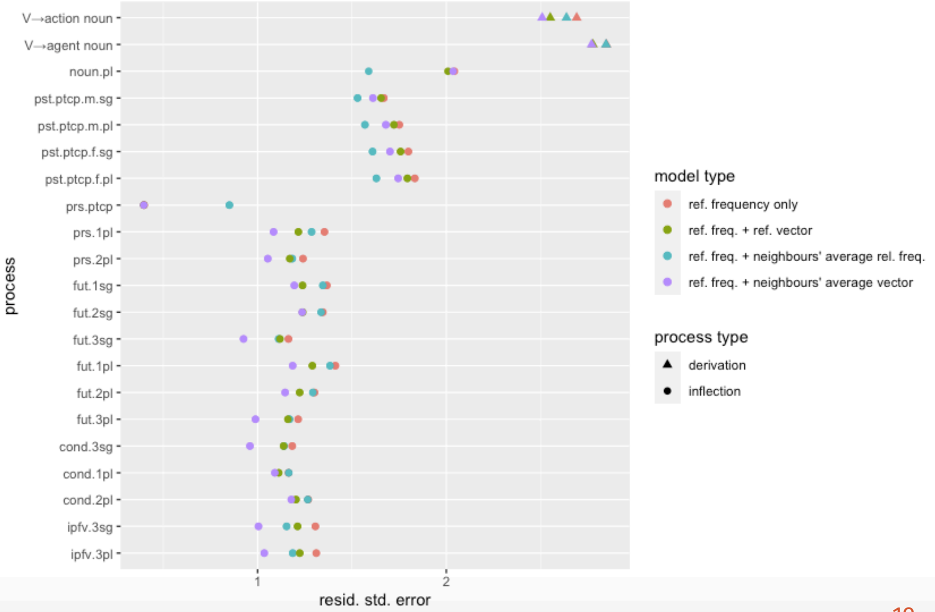
The data

- What morphological processes did we look at?
- Derivation[1]:
  - V $\longrightarrow$ ACTION NOUN
  - V $\longrightarrow$ AGENT NOUN
- Inflection[2]
  - Noun pluralisation
  - 18 verbal inflectional cells (excluded cells with high intraparadigmatic homophony, as frequency counts are unreliable)

[1] Datasets of derivational pairs are scarce, so we were not able to include more. Derivational pairs were selected from Demonette (Hathout and Namer, 2014)

[2] Inflectional pairs were based on the GLàFF (Sajous, Hathout, and Calderone, 2014)

Crunching the numbers



Conclusion

- Theoretically, the distinction between inflection and derivation is quite clear:
  - **Inflection**: different ways to talk about the same concept depending on context
  - **Derivation**: different concepts
- Prediction: qualities of derivational output are harder to predict from the base, compared to inflection. **This is borne out**: all of inflection has a lower RSE than all of derivation.
- The method employed shows promise for **better understanding the nature of different processes**.
  - For past participles, the output has inherently varied semantics, which is why models based on frequency rather than vectors are better predictors

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Data selection

- Which cells in the paradigm of French verbs can we work with?
- Working with our dataset, we exclude…

Finite forms

	1SG	2SG	3SG	1PL	2PL	3PL
IND.PRS	2	3	183	2	5	14
IND.IPFV	0	0	5083	10	10	5076
IND.PST	4484	4448	4694	5116	5116	5101
FUT	5211	5207	5213	5190	5212	5221
SBJV.PRS	0	250	2	8	7	13
SBJV.IPFV	4701	4725	5119	4726	4738	4740
COND	0	0	5220	5212	5212	5215
IMP	—	0	—	2	2	—

Nonfinite forms

INF	PRS.PTCP	PST.PTCP			
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- Bonami and Paperno (2018) test whether this assumption is consistent with distributional semantics
- Assuming it is, we would expect linear offsets for inflectional relations (e.g., $\vec{bare} - \vec{3^{rd}sg}$) to be more consistent than those for derivational relations (e.g., $\vec{verb} - \vec{agent}$)

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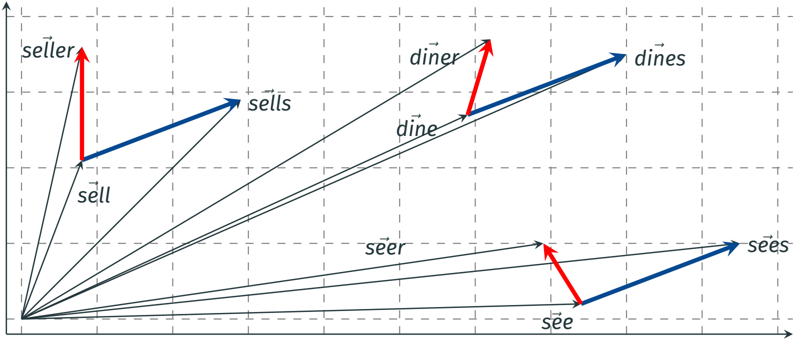

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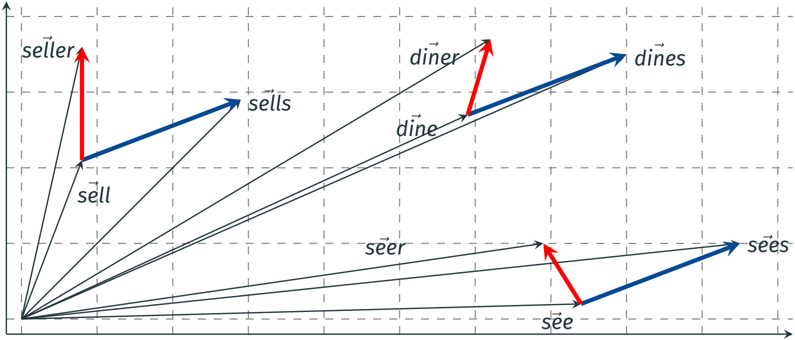

- They find that derivational relations yield significantly more variation than inflectional ones: derivational pairs stray more from the average value than inflectional pairs.