# From world to word:

## Bridging language, culture, and cognition in multilingual contexts

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# Outline:

1. Background
2. Past and ongoing research
   - Semantic representation in bilinguals
   - Lexical attrition: A network approach
   - Emotion semantic networks across cultures
3. Conclusions
4. New directions

# 1. Research background

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- Reality is complex.

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- Language encapsulates reality.

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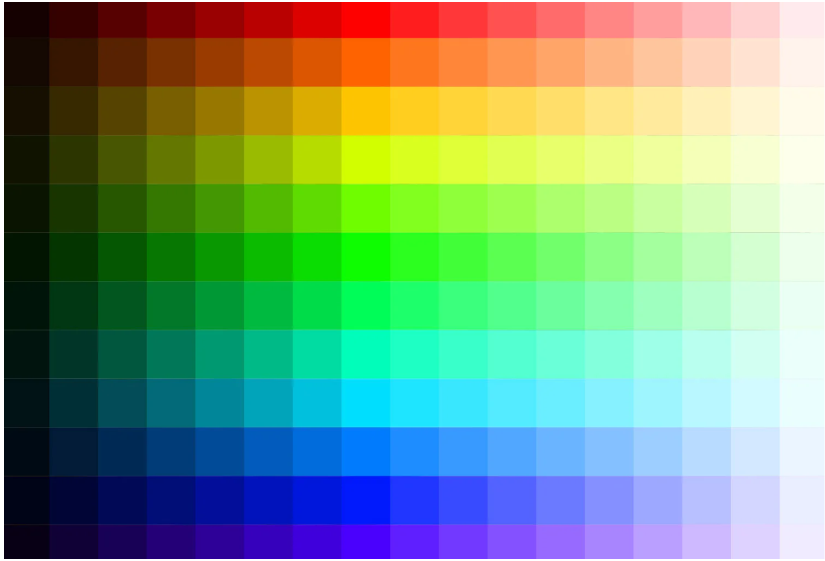
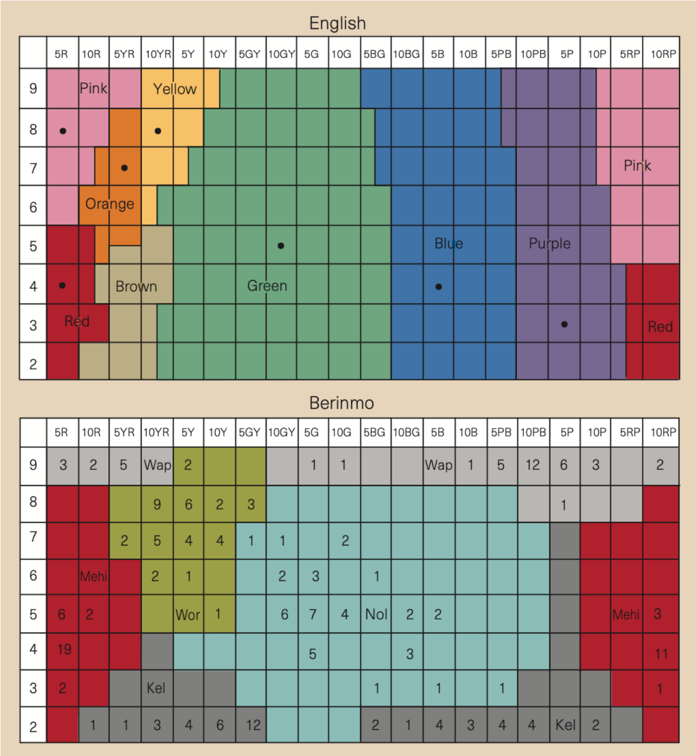
- Reality is complex.
- Language encapsulates reality.
- What is the role of culture?
- Abstract words: "justice" or "beauty."

# Background



Colour spectrum

Davidoff et al. (1999)



# Background

*“[‘szczęśliwy’ , Polish for ‘happy’, has a] much more restricted meaning in Polish.”* (Stanisław Barańczak, in Pavlenko, 2014).

# Background

## Overarching research question:

1. How is **semantic diversity** represented in the **multilingual lexicon** and what are the implications for language processing? How are these dynamics affected by **culture**?

# 2. Past and ongoing research

# Semantic representation in bilinguals

Chaouch-Orozco et al. (2023)

Chaouch-Orozco et al. (in preparation)

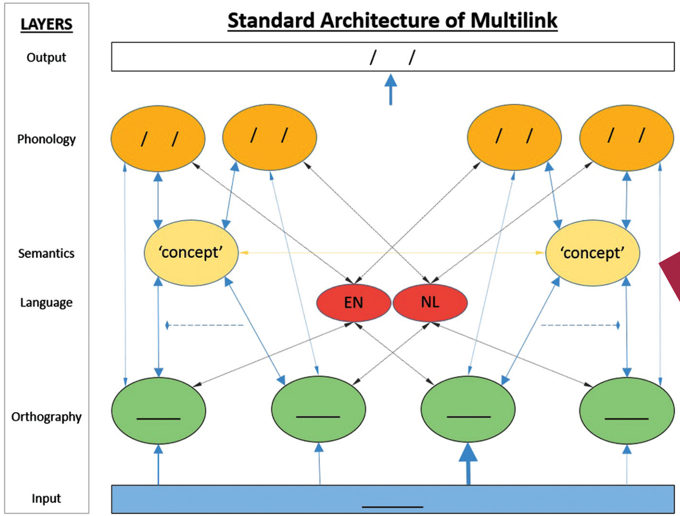
# Are translations *really* equivalent?

- Translation words are regarded as equivalents.

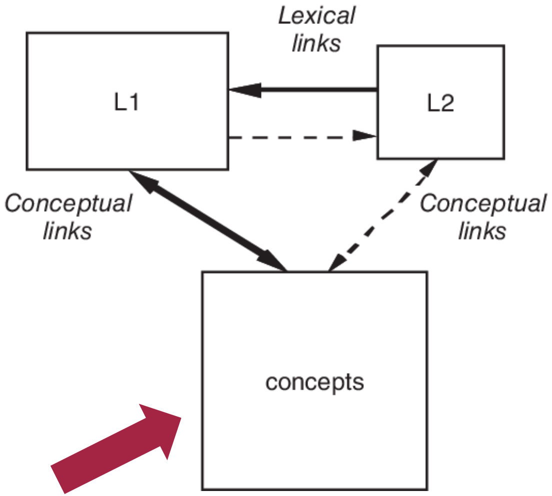
tree – 树 – árbol — arbre – ağaç

# Are translations *really* equivalent?

Most of the bilingual lexical-semantic representation and processing models assume a complete semantic overlap across translations.



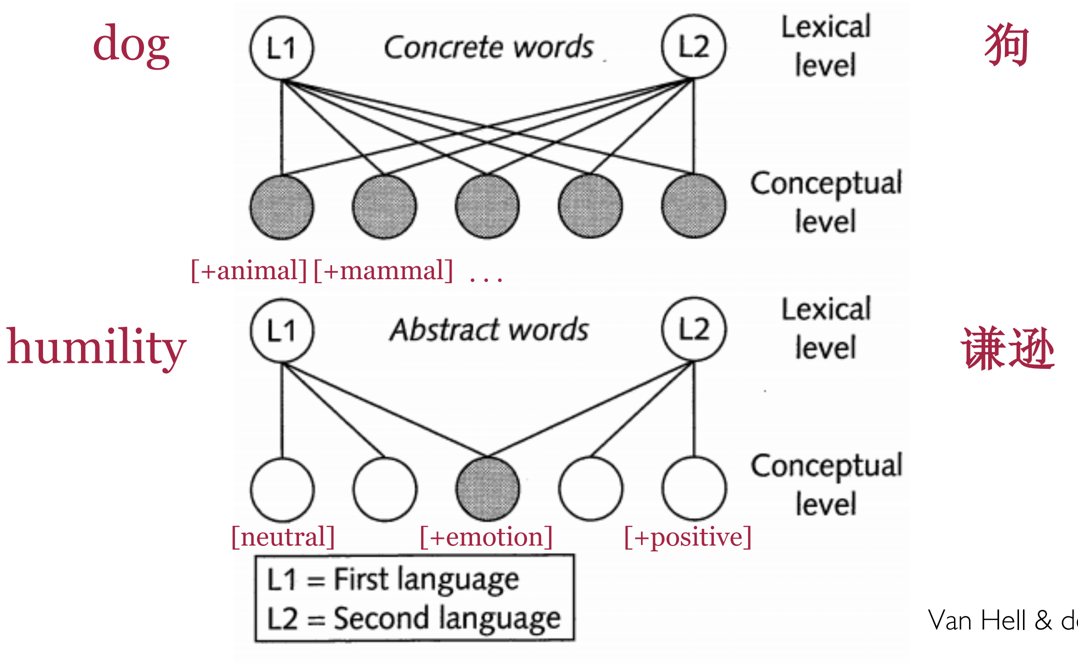

Multilink (Dijkstra et al., 2019)




The Revised Hierarchical Model (Kroll & Stewart, 1994)

# Are translations *really* equivalent?

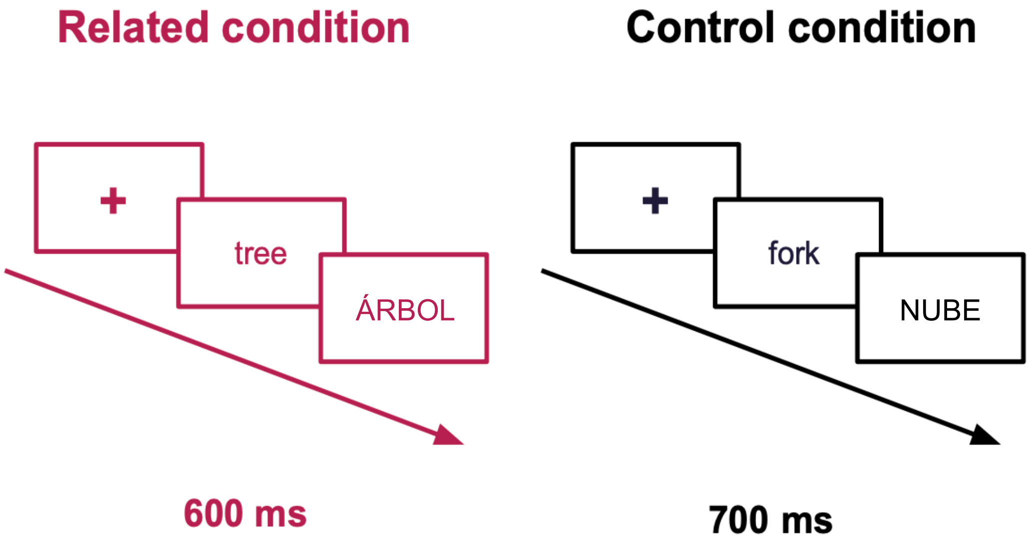
Semantics can be distributed (e.g., the Distributed Feature Model; de Groot, 1992).

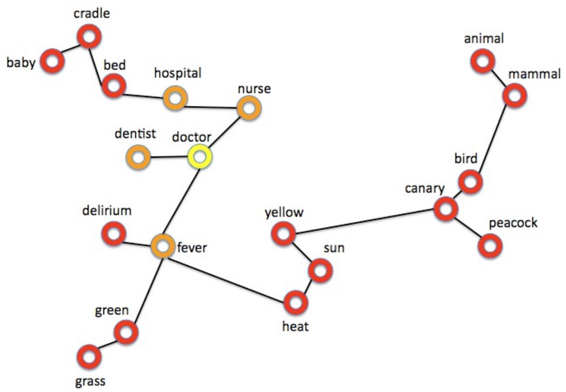



Van Hell & de Groot, (1998)

# Are translations *really* equivalent?

## Chaouch-Orozco et al. (2023):



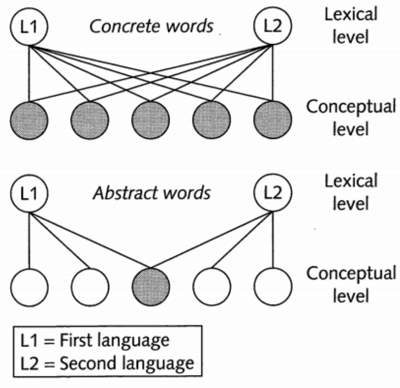
# Are translations *really* equivalent?

## Research question:

Do priming effects differ for concrete and abstract translation pairs?

## Hypothesis:

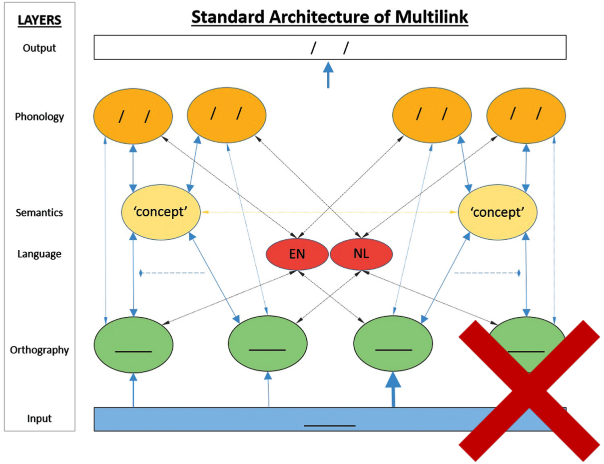
Concrete pairs would elicit larger priming effects because there is larger semantic overlap between them, and more activation is sent from prime to target in related trials.

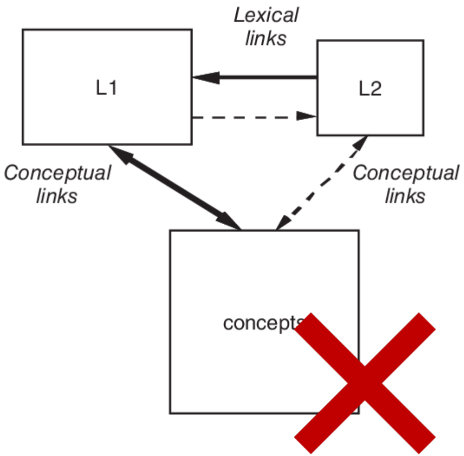


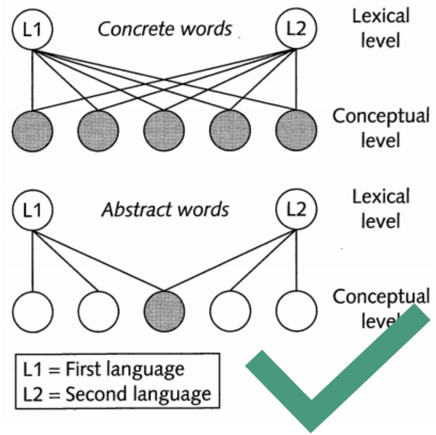
# Translation semantic alignment

## Results:

- Larger priming effects for concrete translation pairs.



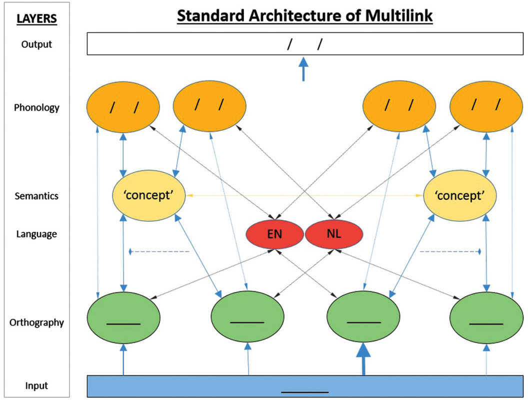



# Translation semantic alignment

## Implication:

- Translations are not equivalent, as predicted by the Distributed Feature Model, and holistic models should reflect this imbalance.
- **How can we improve a computational model like Multilink (Dijkstra et al., 2019)?**



# Translation semantic alignment

## Ongoing follow-up:

- **Research question:** Can we predict priming effects with a quantitative measure (that does not rely on concreteness)?

- **Method:** Calculating a semantic overlap measure based on an algorithm proposed by Thompson et al. (2019) that employs *fastText* word embeddings (Grave et al., 2018).

# Translation semantic alignment

- Based on the distributional hypothesis:

"You shall know a word by the company it keeps" (Firth, 1957)

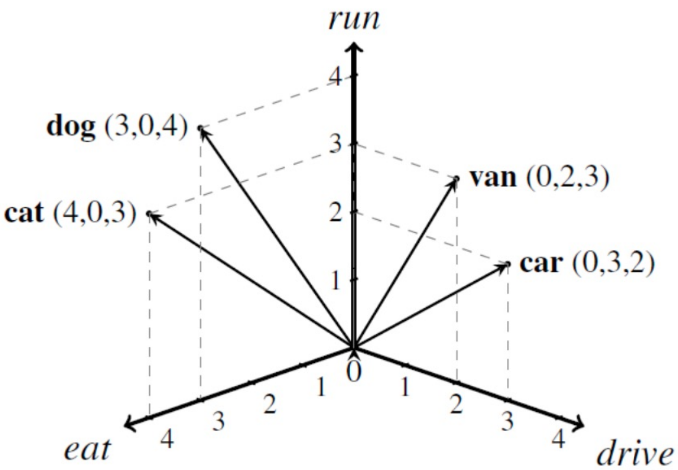
Words occurring in similar contexts have similar meanings. (Harris, 1954)

She bought a ***sofa*** for her living room so she could lie on it.

She bought a ***couch*** for her living room so she could lie on it.

# Translation semantic alignment

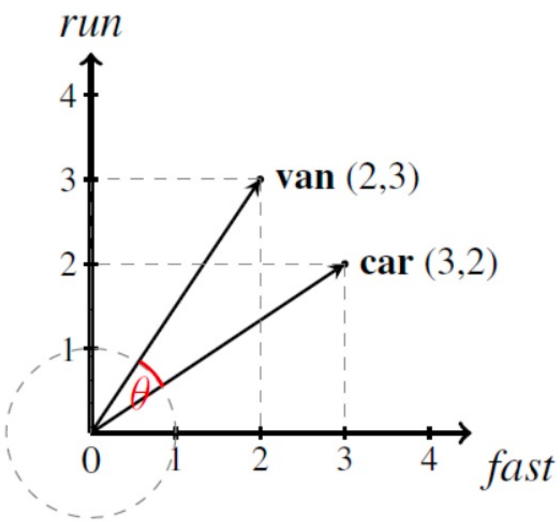
Distributional Models extract vector representations from text corpora



# Translation semantic alignment

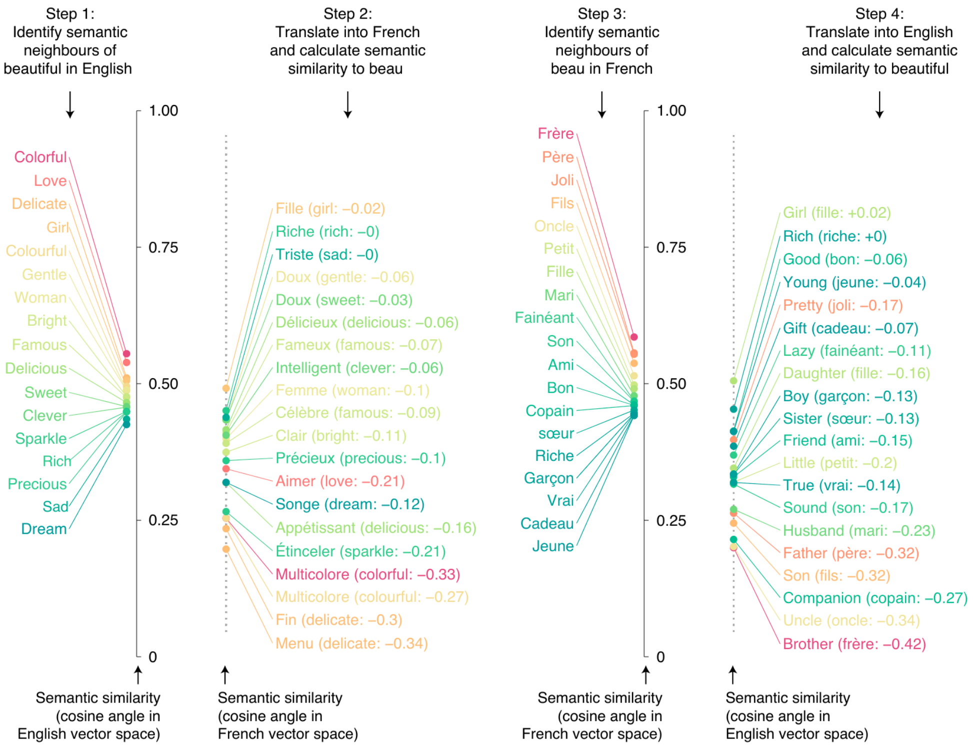
Distributional Models extract vector representations from text corpora

*How similar are van and car?*



# Translation semantic alignment

*How semantically similar are **beautiful** and **beau** (French for "beautiful")?*



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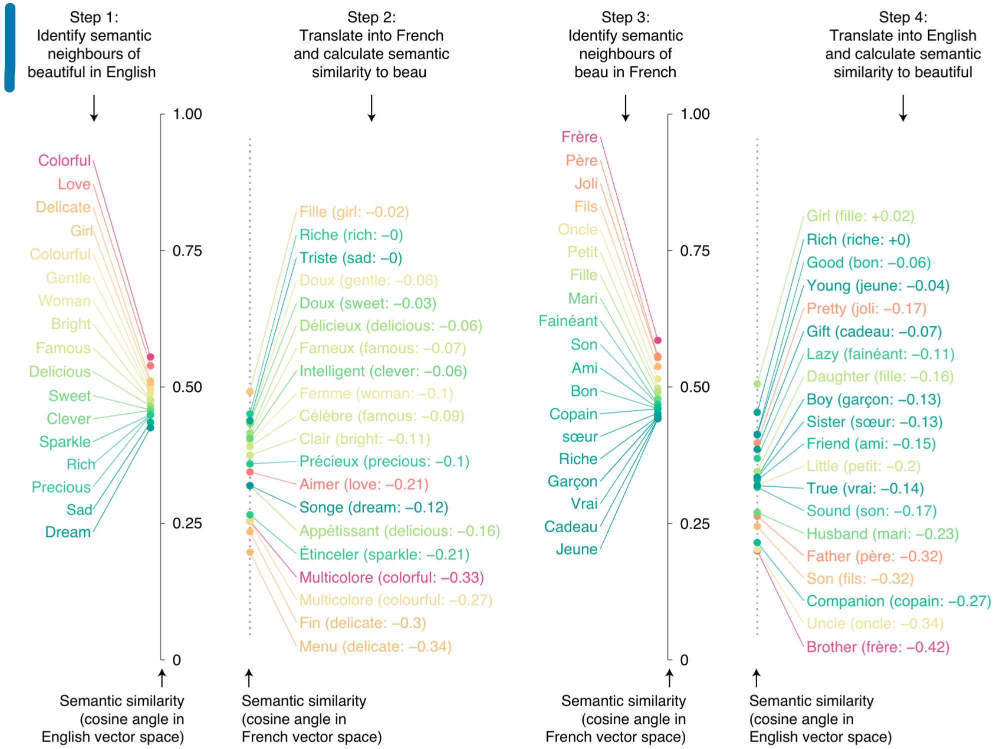

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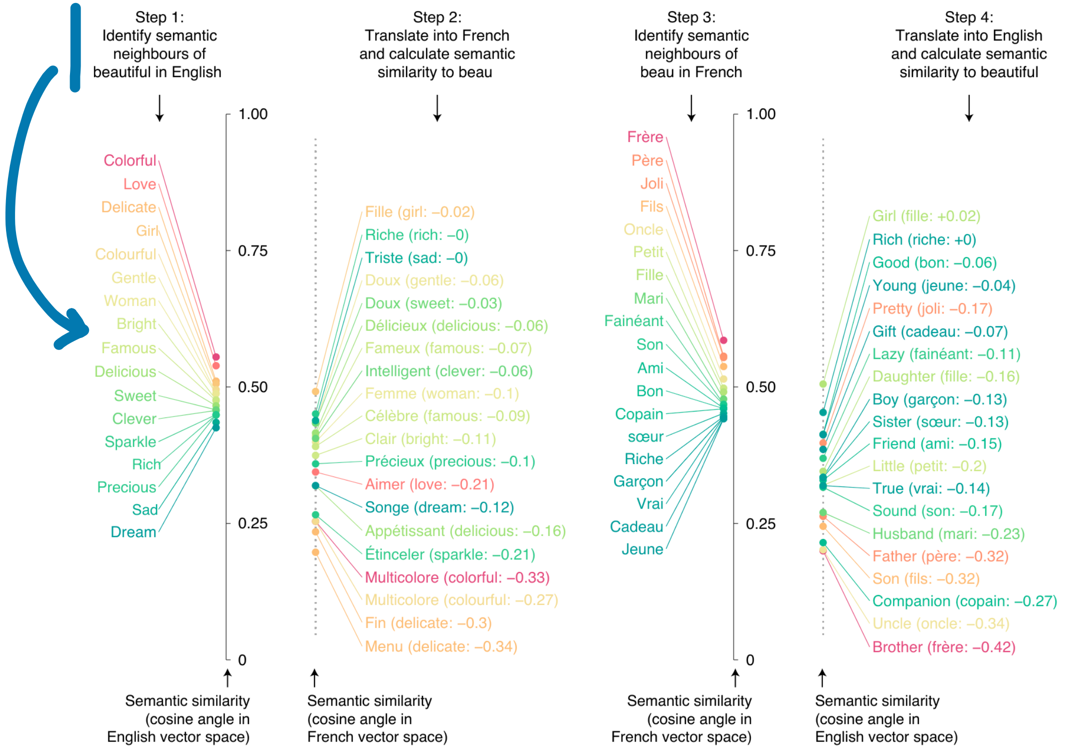

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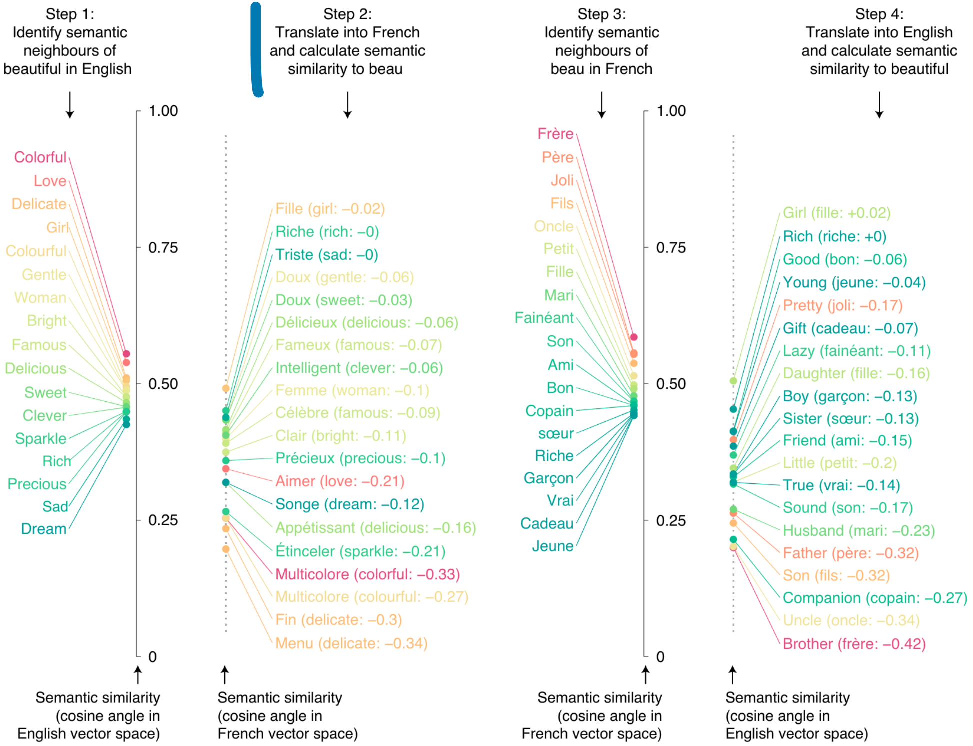

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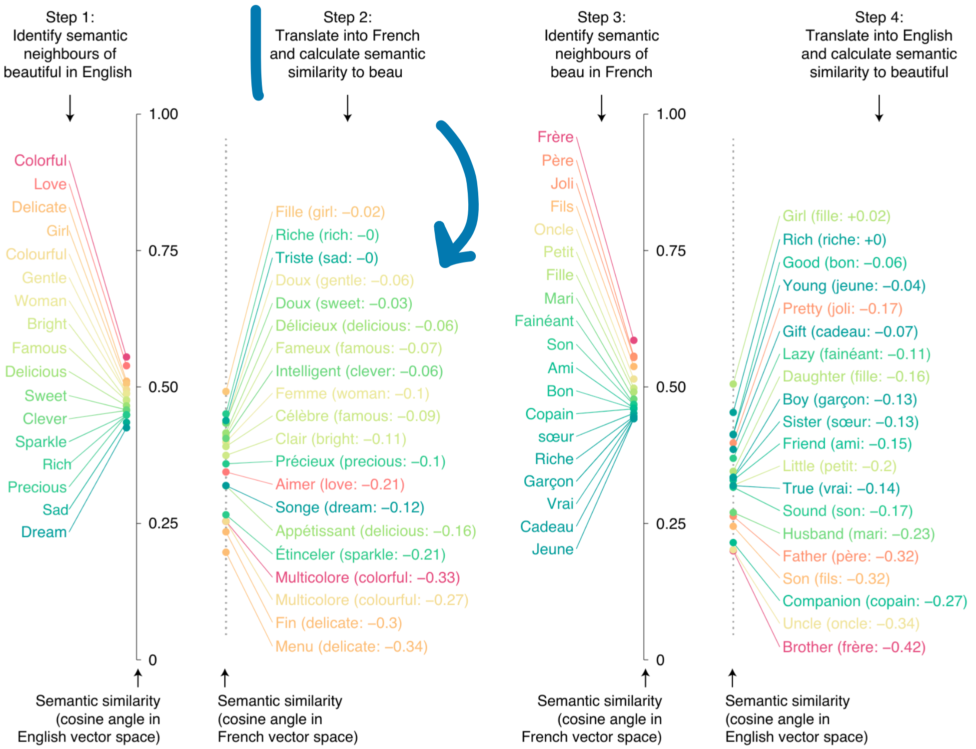

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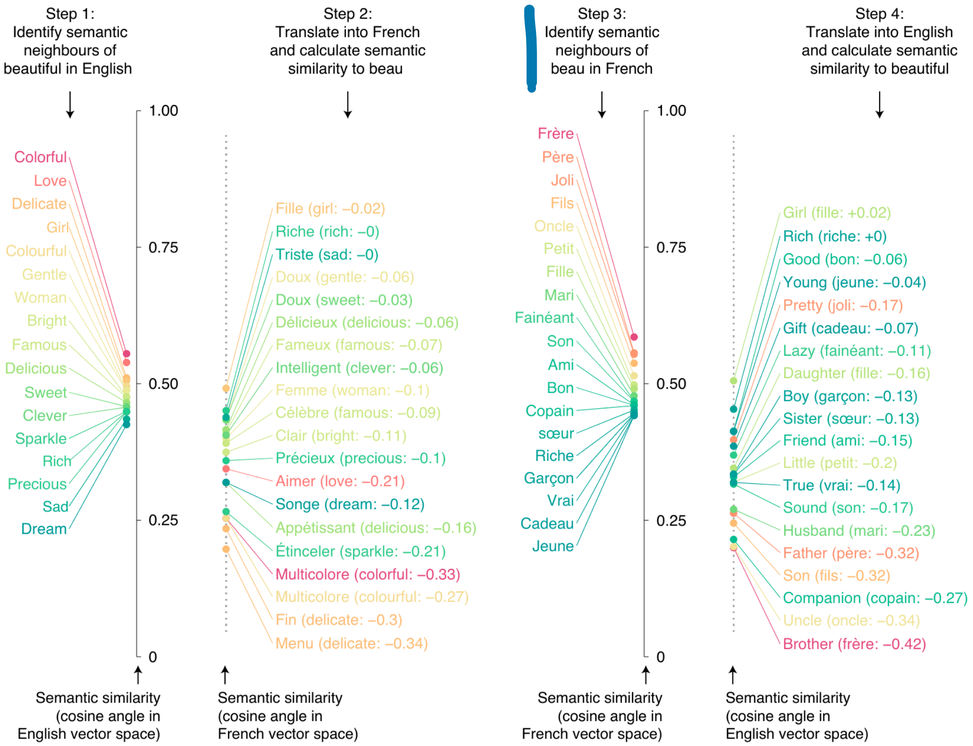

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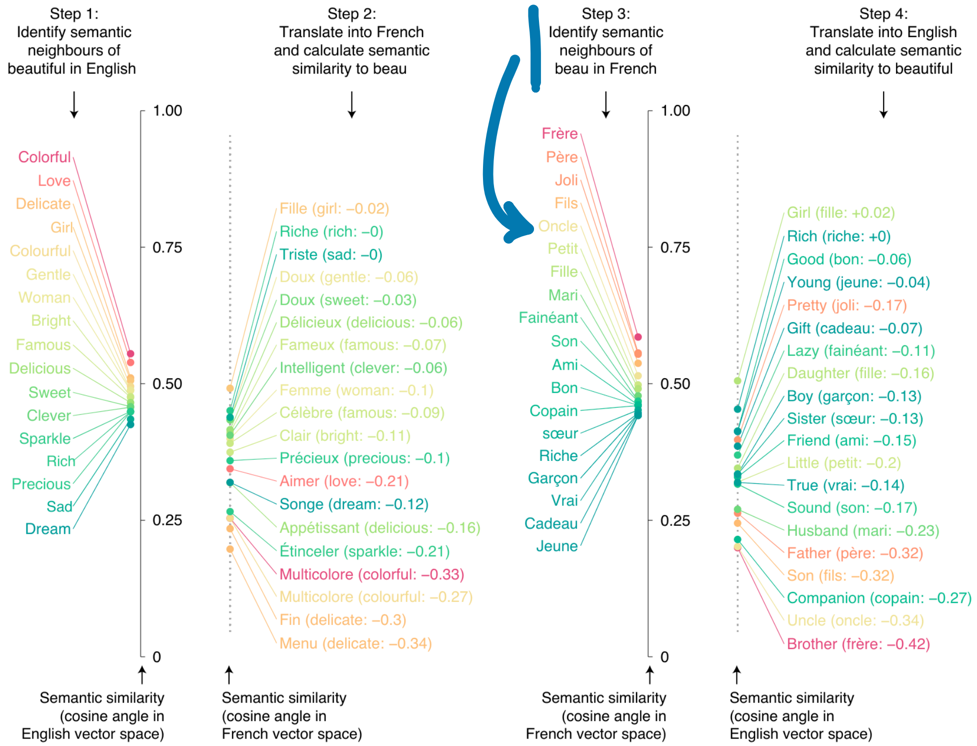

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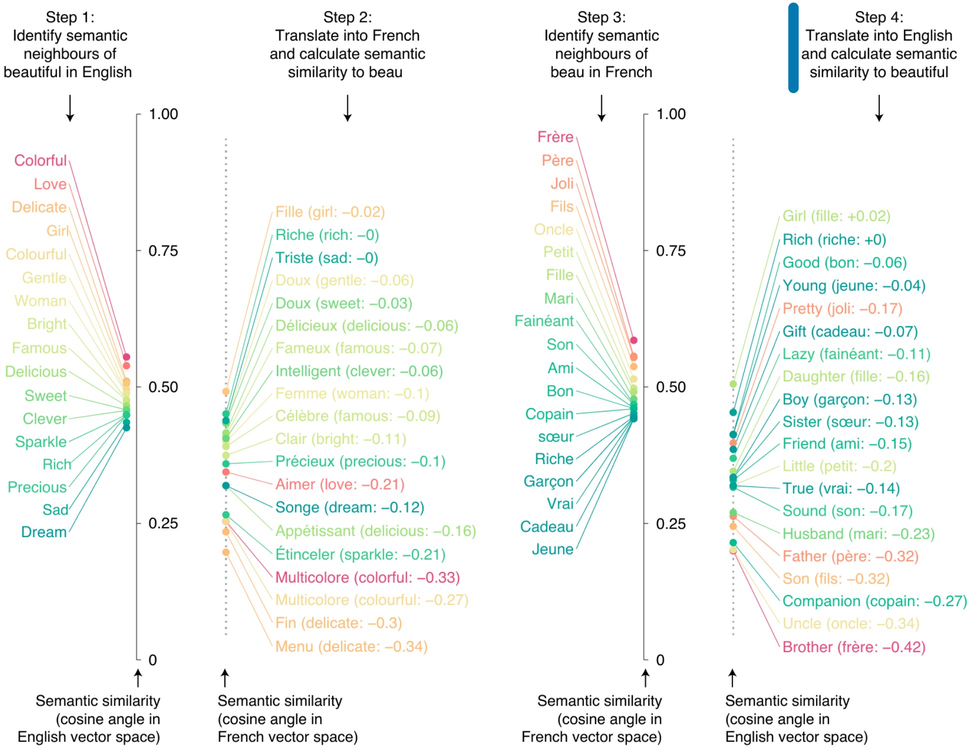

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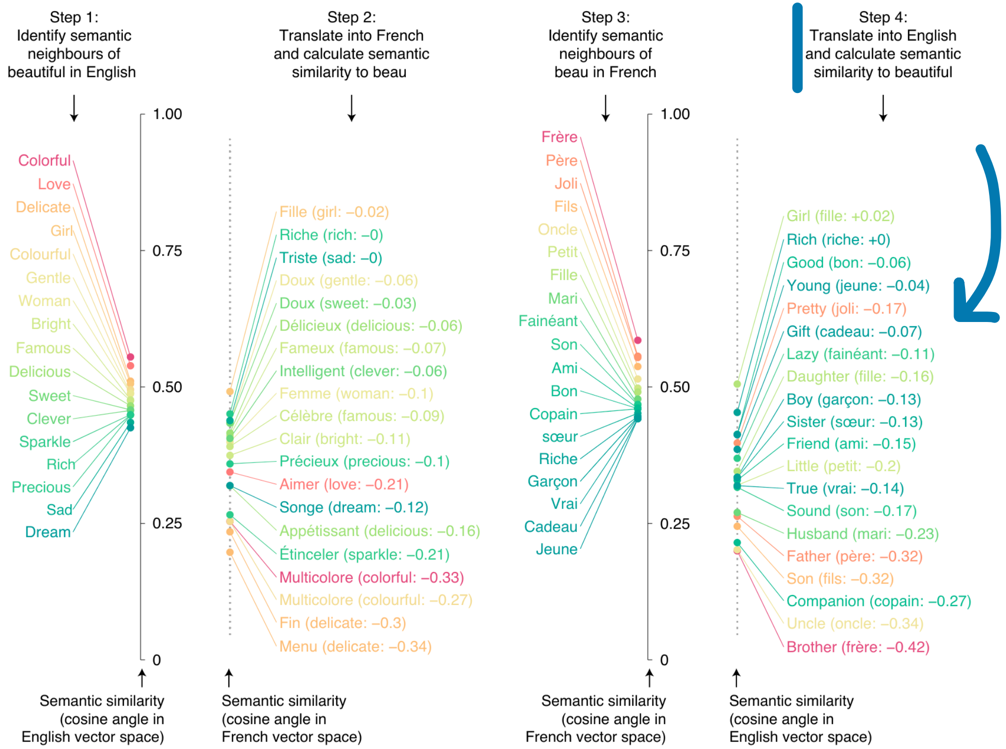
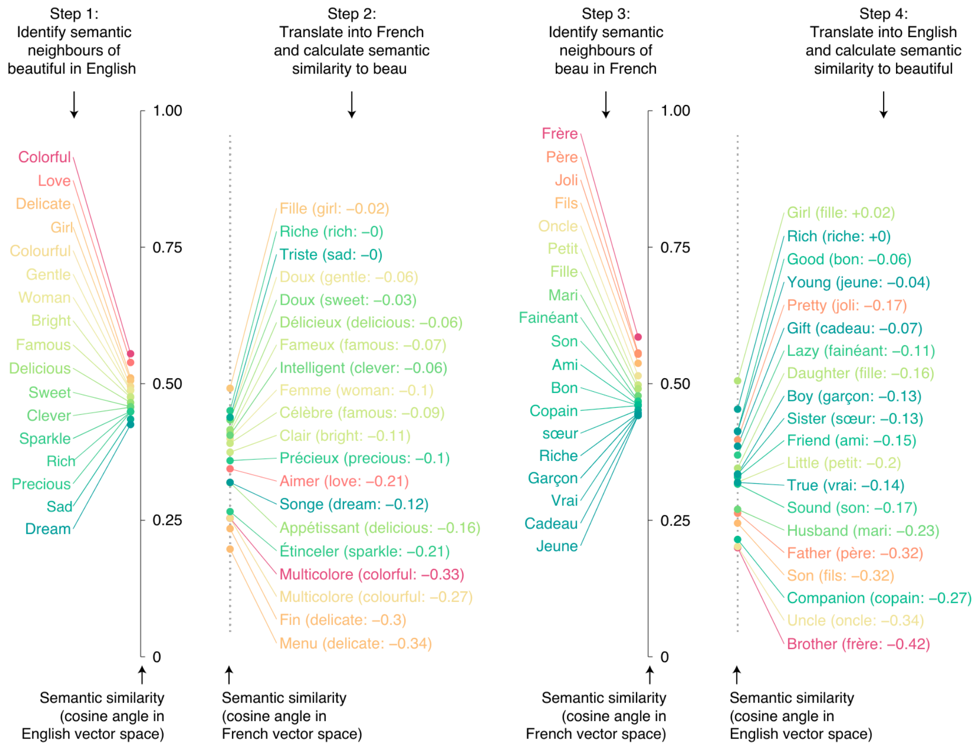


# Translation semantic alignment

*How semantically similar are* ***beautiful*** *and* ***beau*** *(French for "beautiful")?*

*Semantic overlap = 0.56*



# Translation semantic alignment

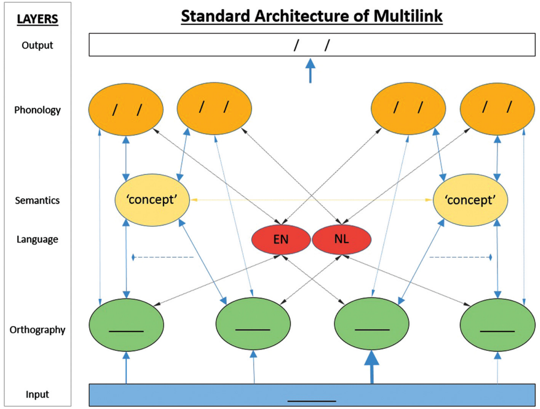
## Preliminary results:

- RTs and priming effects are predicted by the semantic overlap between translations.

# Translation semantic alignment

## Preliminary conclusions:

- Translations equivalents are not really equivalent (confirming findings in Chaouch-Orozco et al., 2023).

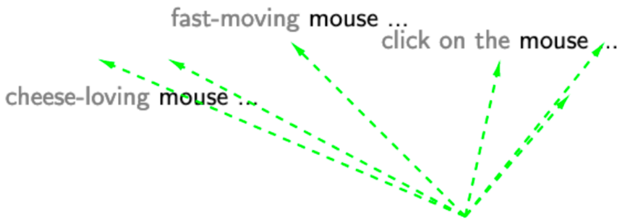



Dijkstra et al. (2019)

# Translation semantic alignment

## Next steps:

- Other approaches (e.g., MUSE).
- Contextualized word embeddings (e.g., BERT).
- More data!




Contextualized word embeddings

# Lexical attrition: A network approach

Chaouch-Orozco and Martín-Villena (2024)

# Lexical attrition

**L1 lexical attrition** (Alternative label: **Reconfiguration**):

The weakening or loss of L1 lexical-semantic abilities due to reduced exposure to the L1 and/or L2 interference.

# Lexical attrition

What is the role of L2 immersion in L1 lexical attrition?

# Lexical attrition

What is the role of L2 immersion in L1 lexical attrition?

Mixed results in previous literature:

- Effects of immersion with short lengths of even three months (e.g., Casado et al., 2023; Linck et al., 2009).
- No effects of immersion after a year of exposure (e.g., Baus et al., 2013; Schmid & Jarvis, 2014).

# Lexical attrition

What may explain divergences across studies?

- Methodological limitations may be behind the inconclusive results.

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- Semantic fluency is often used in L1 lexical attrition studies to tap into semantic structure and processing.

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What may explain divergences across studies?

- Methodological limitations may be behind the inconclusive results.
- Semantic fluency is often used in L1 lexical attrition studies to tap into semantic structure and processing.
- However, current analyses present critical drawbacks.
  - Word counts and time-course analysis do not capture semantic structural properties.
  - Clustering helps identify the grouping of words within the semantic space (e.g., African animals), but semantic categories are inherently subjective.

# Lexical attrition

Leveraging network science tools for studying lexical attrition

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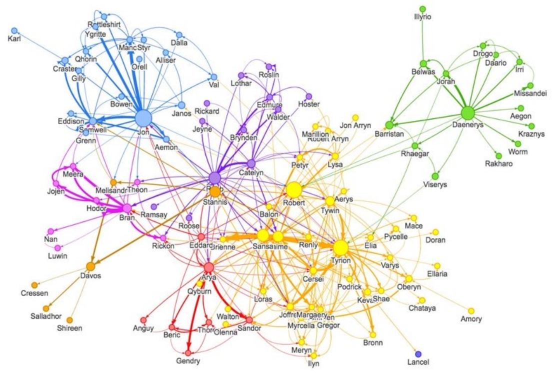
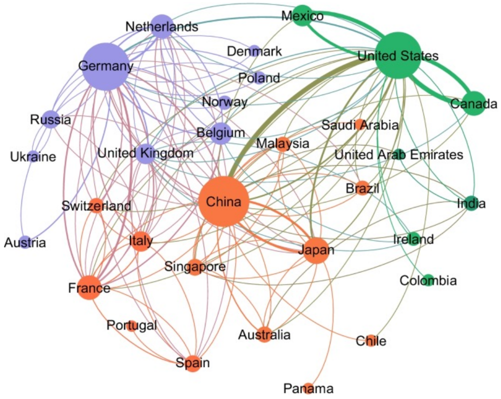
Leveraging network science tools for studying lexical attrition

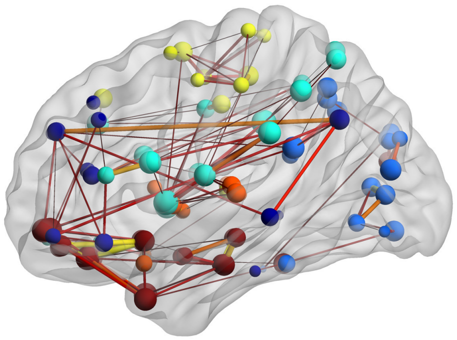
- Networks (complex systems) are everywhere.



Social network




Trade network



Brain network

# Lexical attrition

Leveraging network science tools for studying lexical attrition

- This approach nicely fits the long-standing assumption that our lexicons function as networks (Collins & Loftus, 1975).

# Lexical attrition

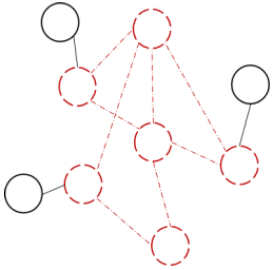
Leveraging network science tools for studying lexical attrition

- This approach nicely fits the long-standing assumption that our lexicons function as networks (Collins & Loftus, 1975).
- Relevant contributions to our understanding of the lexicon (e.g., Castro & Siew, 2020; Xu et al., 2021; Steyvers & Tenenbaum, 2005).

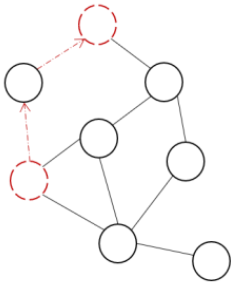
# Lexical attrition

Three critical indices of structural organization

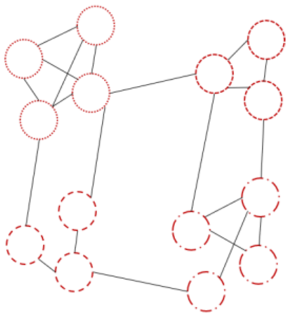
- Clustering coefficient (CC)
- Average shortest-path length (ASPL)
- Modularity (Q)



Cluster coefficient (CC)



Shortest Path Length (SPL)

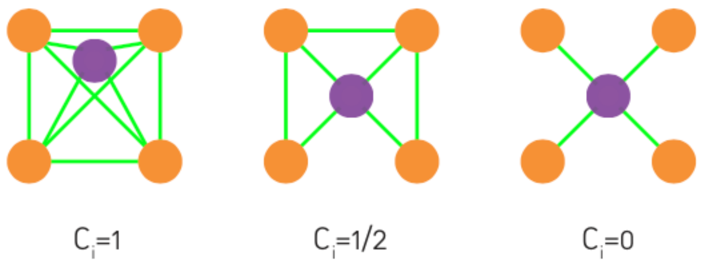


Modularity (Q)

# Lexical attrition

Three critical indices of structural organization

- Clustering coefficient (CC): the degree to which nodes tend to group together.

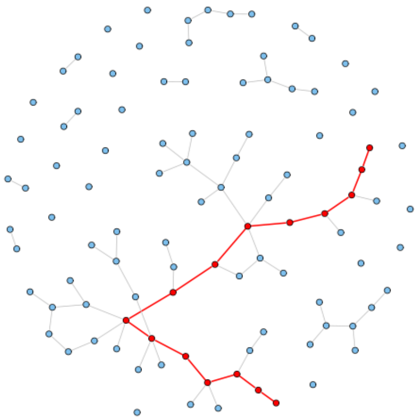


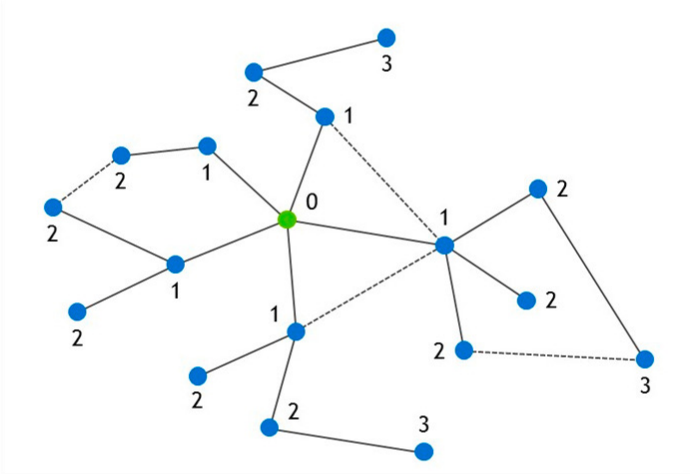

Barabási (2012)

# Lexical attrition

Three critical indices of structural organization

- Average shortest-path length (ASPL): the average distance between each pair of nodes.

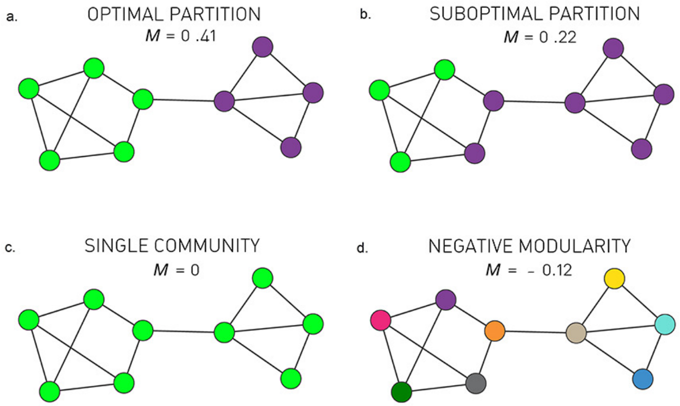




# Lexical attrition

Three critical indices of structural organization

- Modularity (Q): the degree to which the network comprises distinct communities.

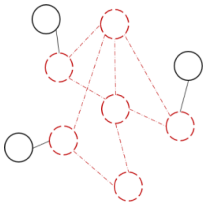



Barabási (2012)

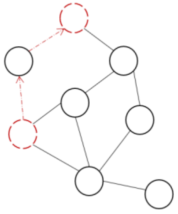
# Lexical attrition

## Three critical indices of structural organization

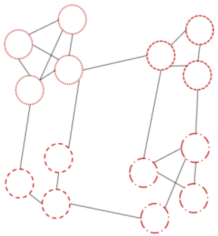
- High clustering coefficient (CC) → Better semantic organization in monolinguals (Christensen et al., 2018; Cosgrove et al., 2021), and in the L2 of bilinguals (Feng & Liu, 2023).
- Low average shortest-path length (ASPL) → Faster navigability within the lexicon (Siew et al., 2019; Siew & Guru, 2023).
- Optimal modularity (Q) → Increased knowledge (Siew & Guru, 2023) and creativity (Kenett et al., 2014).



Cluster coefficient (CC)



Shortest Path Length (SPL)



Modularity (Q)

# Lexical attrition

## Research question:

- Does L2 immersion erode the L1 network's organization, as reflected by lower CC, and higher ASPL and Q values?

## Method:

- 94 immersed and 80 non-immersed Spanish-English late sequential bilinguals.
- The participants' L2 proficiency was matched across groups.
- Two semantic fluency tasks: fruits and vegetables (L1), animals (L2) → Correlation networks (Kenett et al., 2013).

# Lexical attrition

## Results:

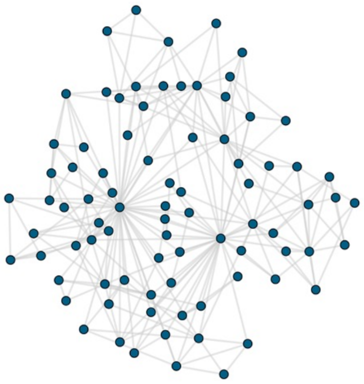
- The L2 networks of the immersed participants displayed better organization (higher CC, lower ASPL and Q values). Critically, this serves as proof of concept for our methodology.

# Lexical attrition

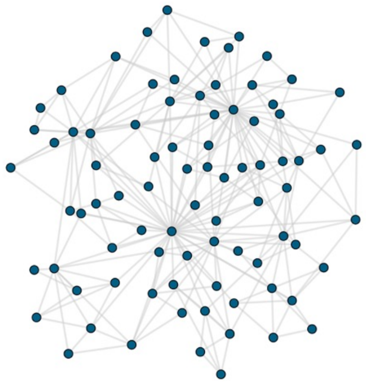
## Results:

- The L1 networks of the immersed participants showed early effects of L1 lexical attrition (lower CC, higher ASPL and Q values).

**L1 networks**



L2 immersed
(people using more the L2)



Non-immersed

# Lexical attrition

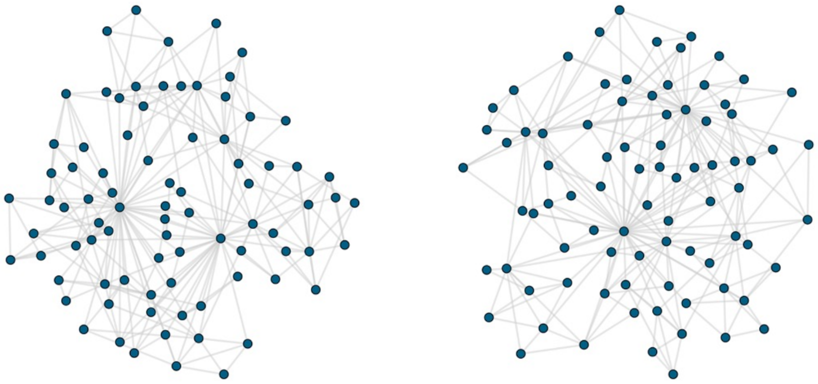
## Results:

- The L1 networks of the immersed participants showed early effects of L1 lexical attrition (lower CC, higher ASPL and Q values).

Two important notes about the L1 attrition effects:

- We did not observe them in more traditional analyses.
- They were larger with increased length of immersion.

**L1 networks**



L2 immersed
(people using more the L2)

Non-immersed

# Lexical attrition

## Results:

- The L1 attrition effects unfold **gradually**.

Clustering coefficient
(reduced connectedness)

Modularity
(reduced integration)

Average shortest-path length
(reduced navigability)

# Lexical attrition

## Discussion:

- Immersion in an L2-dominant environment results in changes in the structural organization of the native semantic system.

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# Lexical attrition

## Discussion:

- Immersion in an L2-dominant environment results in changes in the structural organization of the native semantic system.
- Crucially, traditional analyses do not capture these changes.
- Network science provides robust techniques to investigate these subtle dynamics.

# Lexical attrition

Introducing the Lexical Attrition Foundation (LeAF) framework:

## The LeAF framework

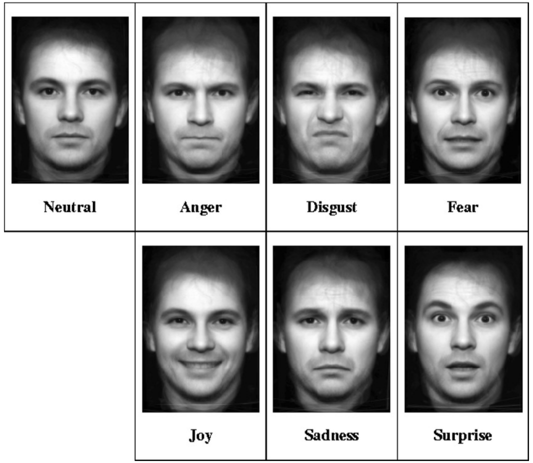
| **Hierarchy of changes** | **Processing effects** |
| --- | --- |
| Clustering coefficient (reduced connectedness) | Hesitations, pauses, circumlocutions |
| Modularity (reduced integration) | Lexical substitutions, semantic inaccuracy, L2 borrowings |
| Average shortest-path length (reduced navigability) | Retrieval slowing down, repetitions, language switches |

# Emotion semantic networks across cultures

Chaouch-Orozco et al. (in preparation)

# Emotion semantic networks

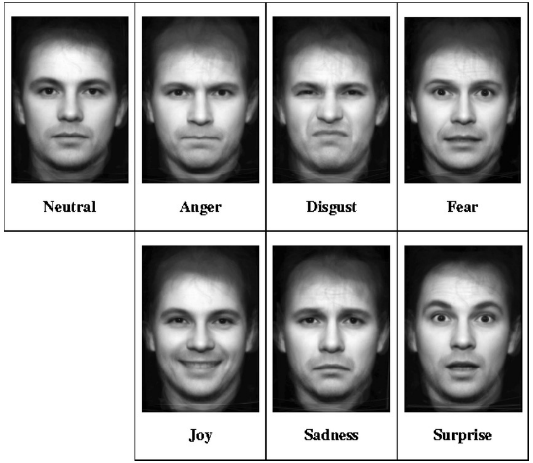
- Universalists regard emotions as **natural kinds**: biologically determined physiological responses that are universally found across cultures (Ekman, 1992).




Ekman (1996)

# Emotion semantic networks

- Universalists regard emotions as natural kinds: biologically determined physiological responses that are universally found across cultures (Ekman, 1992).
- For psychological constructionists, emotions represent culturally rooted categories of core affect (valence and arousal).
  - Emotions are social constructs.

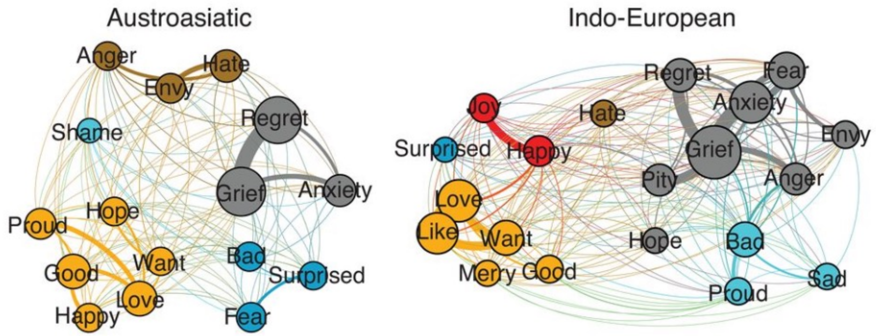



Ekman (1996)

# Emotion semantic networks

## Jackson et al. (2019):

- Colexification networks across 20 language families and more than 2,000 languages.
- Through a clustering analysis, they observed a clear effect of cultural relatedness, as proxied by geographical distance.




Jackson et al. (2019)

# Emotion semantic networks

- Limitations of Jackson et al.'s approach:
  - Colexified concepts may not fully capture the relationships between emotions.
  - Colexification does not allow building language-specific networks.
- **Why is this important?**
  1. Language-specific networks allow for the examination of language evolution patterns alongside the specific cultural factors shaping them.

# Emotion semantic networks

## Method:

- 50 native speakers of 15 languages from diverse language families (spanning Europe and Asia).
- Participants completed a spatial arrangement task (Q-SpAM; Koch et al., 2022) with 47 emotion words.
- Cultural relatedness was proxied by geographical distance (Eff, 2008; Jackson et al., 2019) and differences in Hofstede's cultural dimensions (Hofstede, 2001) and religion/philosophical traditions.

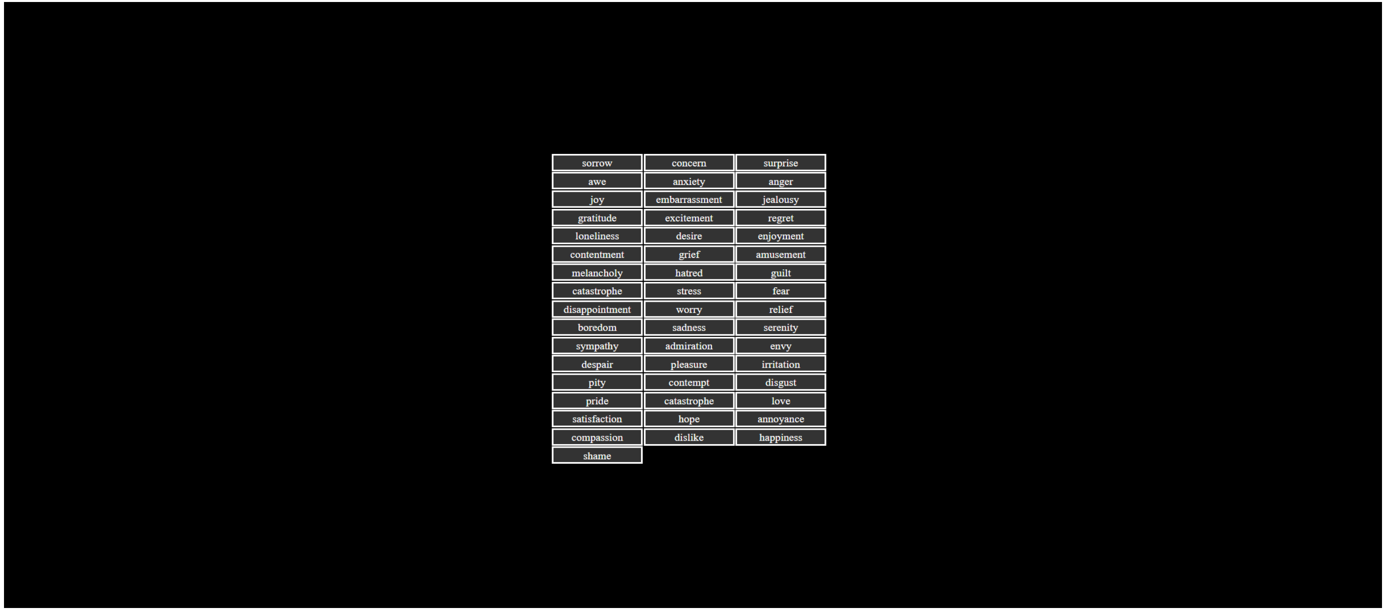
# Emotion semantic networks

## Method:

- Hofstede's cultural dimensions:
  - Power distance: Acceptance of power inequality.
  - Individualism: Priority of the individual over the group.
  - Uncertainty avoidance: Degree of comfort with ambiguity and change.
  - Masculinity vs feminity: Clearly distinct gender roles.
  - Long- vs short-term orientation: Focus on future vs present.
  - Indulgence: Free gratification of desires.

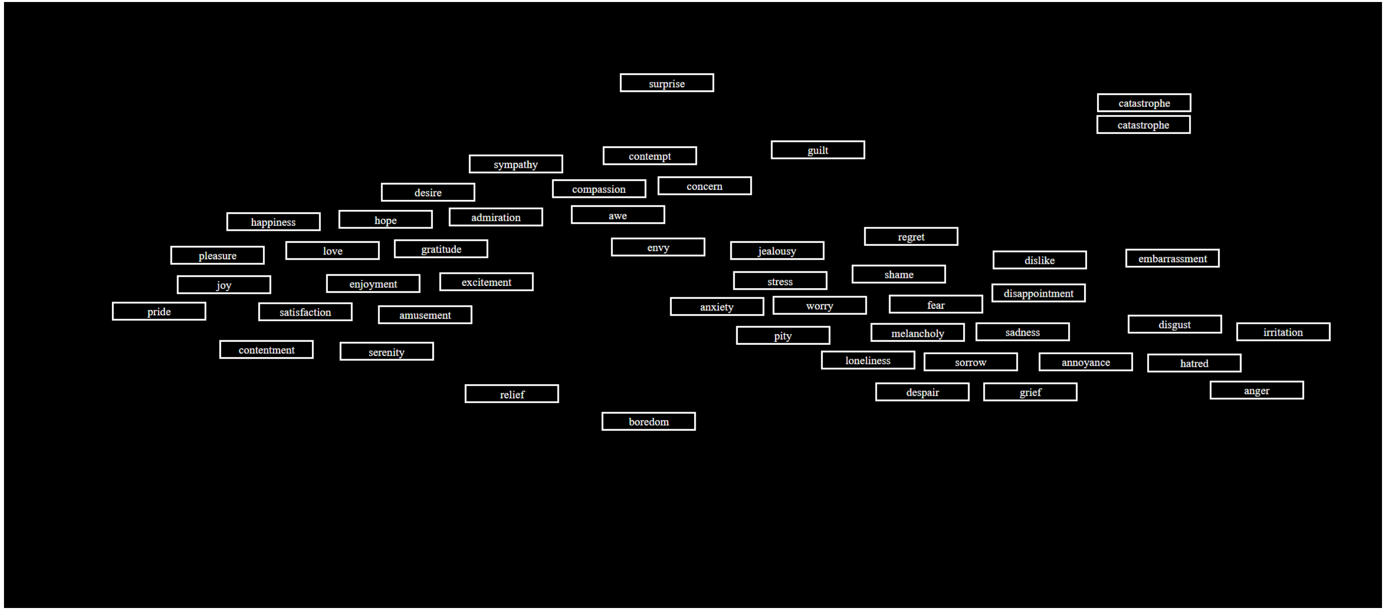
# Emotion semantic networks

## Q-SpAM (Koch et al., 2022):

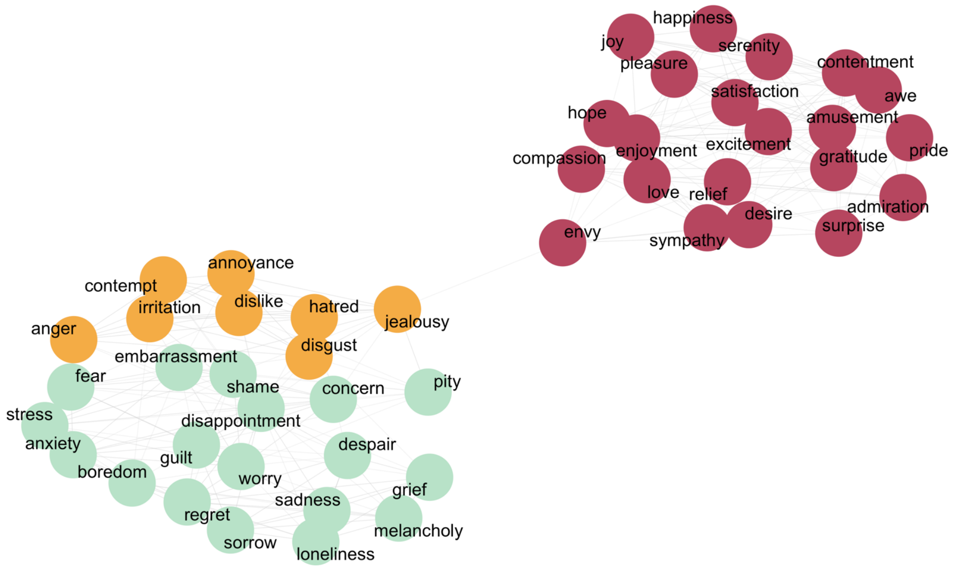


# Emotion semantic networks

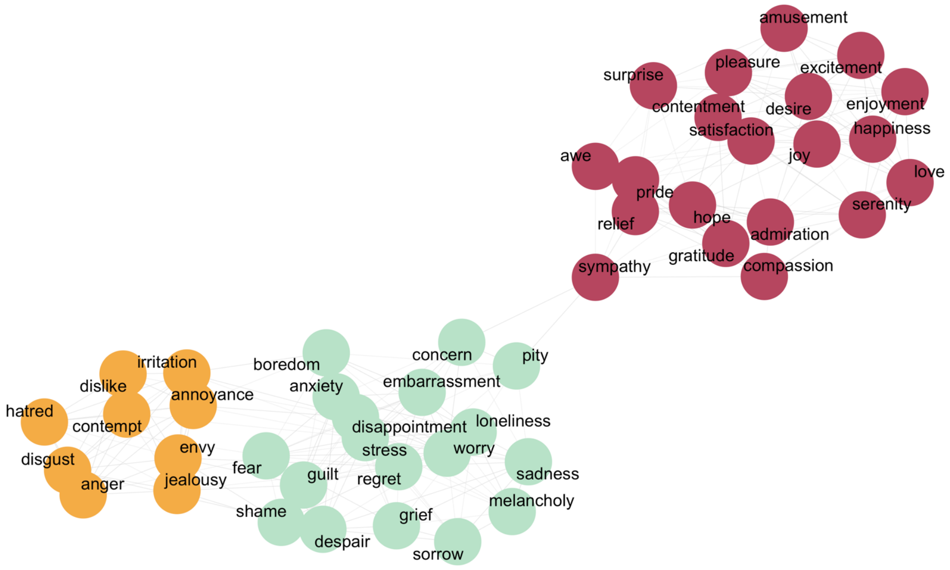
## Q-SpAM (Koch et al., 2022):



# Emotion semantic networks



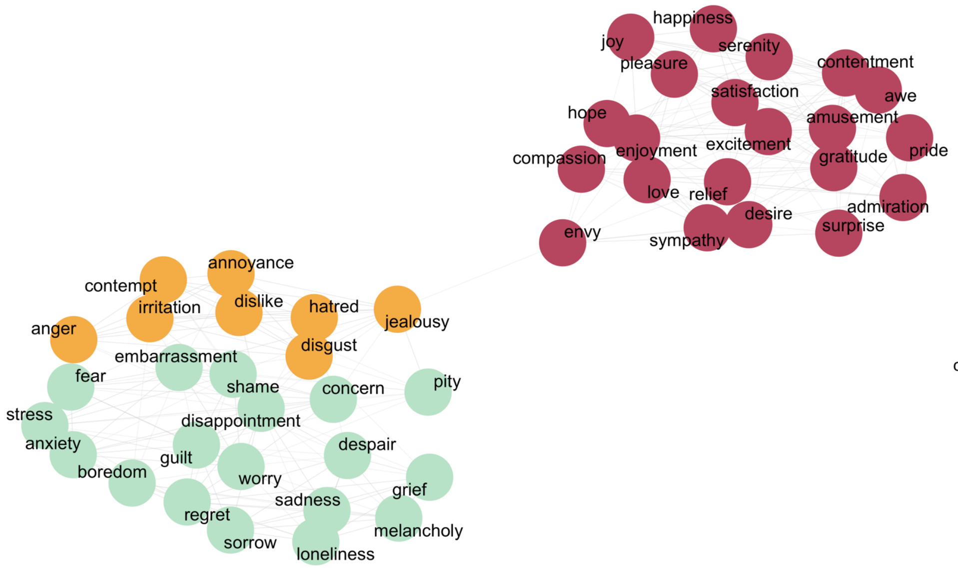

English emotion network



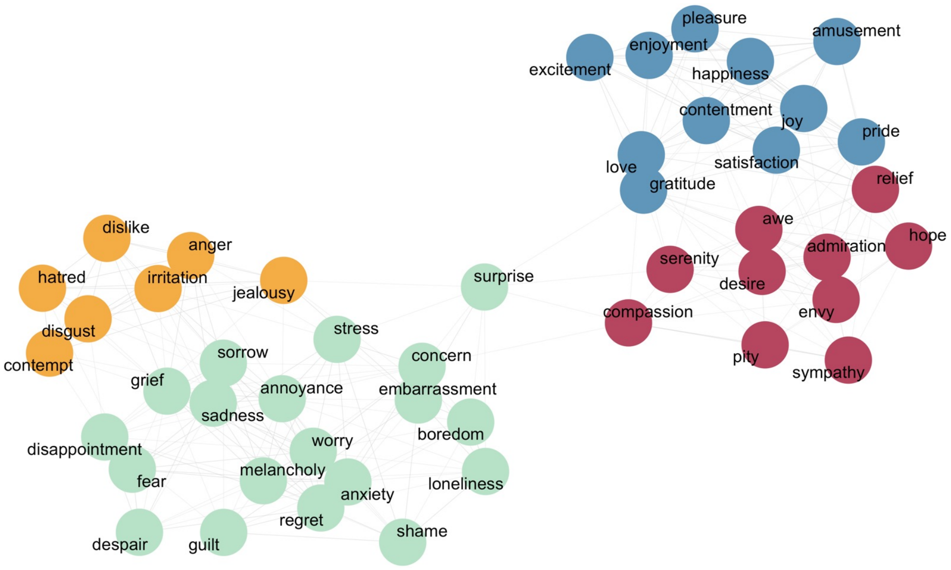

Hungarian emotion network

Adjusted Rand Index: 0.46

# Emotion semantic networks




English emotion network

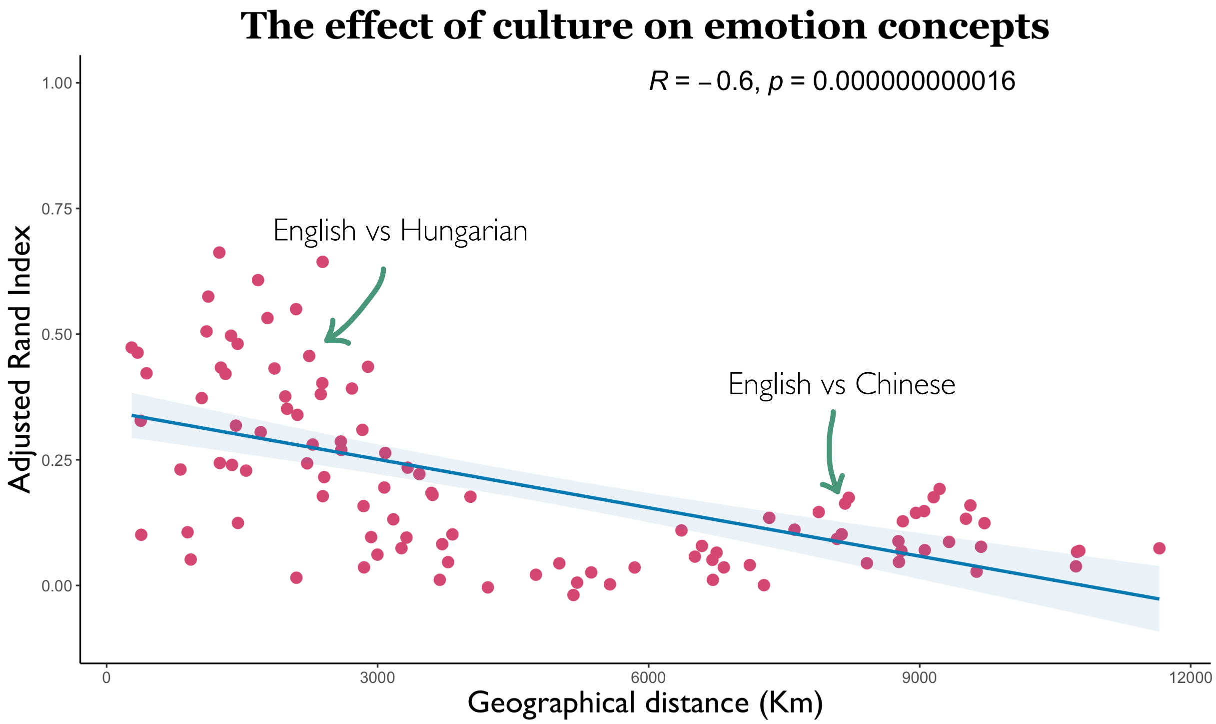



Chinese emotion network

Adjusted Rand Index: 0.21

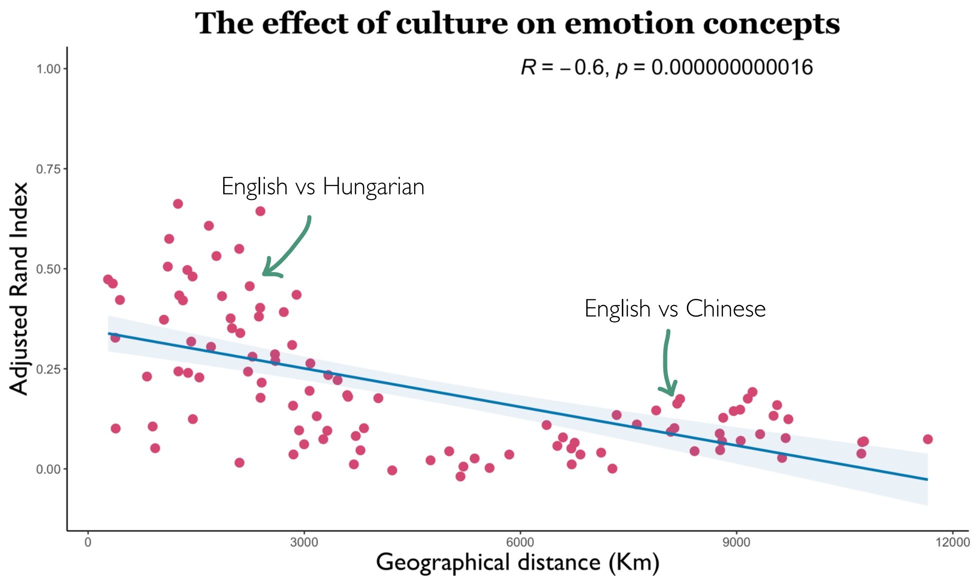
# Emotion semantic networks

## Results:



# Emotion semantic networks

## Results:




- Significant effect of culture: Languages spoken in more related cultures exhibit more similar emotion semantic networks.
- No effects of **language family** or **script**.
- Two cultural dimensions stand out: Long-term orientation and religion.
- BUT the effect seems to be driven by the negative emotion words.

# Emotion semantic networks

## Discussion:

- As argued by constructionist theories, culture influences emotion semantic spaces, with long-term orientation and the predominant religion being the most relevant factors.

# 3. Conclusions

# Emotion semantic networks

## Overarching conclusions:

- How is **semantic diversity** represented in the multilingual lexicon and what are the implications for language processing? And how are these dynamics affected by **culture**?

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# Emotion semantic networks

## Overarching conclusions:

- How is **semantic diversity** represented in the multilingual lexicon and what are the implications for language processing? And how are these dynamics affected by **culture**?

    1. Translations are not equivalent: Culture determines how we categorize reality *in very specific ways.*

    2. Computational models of the multilingual lexicon (e.g., Multilink; Dijkstra et al., 2019) should incorporate distributed semantic representations.

    3. Bi-/multilinguals are affected by these misalignments (LeAF framework).

# This wouldn’t have been possible without…

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# 4. New directions

# New directions

## Representational and processing dynamics in multilinguals:

1. Testing the LeAF framework in processing tasks.

### The LeAF framework

| Hierarchy of changes | | Processing effects |
|---|---|---|
| Clustering coefficient (reduced connectedness) | → | Hesitations, pauses, circumlocutions |
| ↓ | | |
| Modularity (reduced integration) | → | Lexical substitutions, semantic inaccuracy, L2 borrowings |
| ↓ | | |
| Average shortest-path length (reduced navigability) | → | Retrieval slowing down, repetitions, language switches |

# New directions

**Representational and processing dynamics in multilinguals:**

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2. Integrating phonological and orthographic information.

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**Representational and processing dynamics in multilinguals:**

1. Testing the LeAF framework in processing tasks.
2. Integrating phonological and orthographic information.
3. Going beyond lexical attrition: Examining different bi-/multilingual experiences in Hong Kong:
    - Heritage bilinguals, late sequential bilinguals, multilinguals…
    - Different language combinations: effects of typology.

# New directions

## **Emotion semantic representation and processing:**

1. Examining emotion semantics across cultures with **different types of data.**
   - Word embeddings (with Emmanuele Chersoni and Jakob Prange).
   - Word association models (with Simon De Deyne—*Small World of Words*; De Deyne et al., 2019).

# New directions

## Emotion semantic representation and processing:

1. Examining emotion semantics across cultures with **different types of data.**
   - Word embeddings (ongoing work with Emmanuele Chersoni and Jakob Prange).
   - Word association models (with Simon De Deyne—*Small World of Words*; De Deyne et al., 2019).
2. Why do negative emotion words show greater semantic evolution?
   - Potential factors driving the effect:
     - Cultural dimensions.
     - Allostatic dysregulation (response to stress).
     - The "range effect" (Alves et al., 2017).
   - Semantic evolution in the lab.

The range effect:

*"All happy families are alike; each unhappy family is unhappy in its own way"*

(Lev Tolstoy)

# New directions

## Emotion semantic representation and processing:

3. Studying multilingual and clinical populations in Hong Kong.
    - Emotion semantic representation influences emotional processing (Gendron et al., 2012, 2013; Lindquist et al., 2006).
    - Pilot studies in some Capstone projects.
    - Autistic children (with Yixin Zhang).
    - The Hong Kong Emotion Map: Emotion semantic representation and mood disorders.
        - Semantic and associative relationships.
        - Emotional granularity.
        - Thought processes and rumination.

# Thank you!

# Questions?