



Does semantic adaptation predict semantic change?

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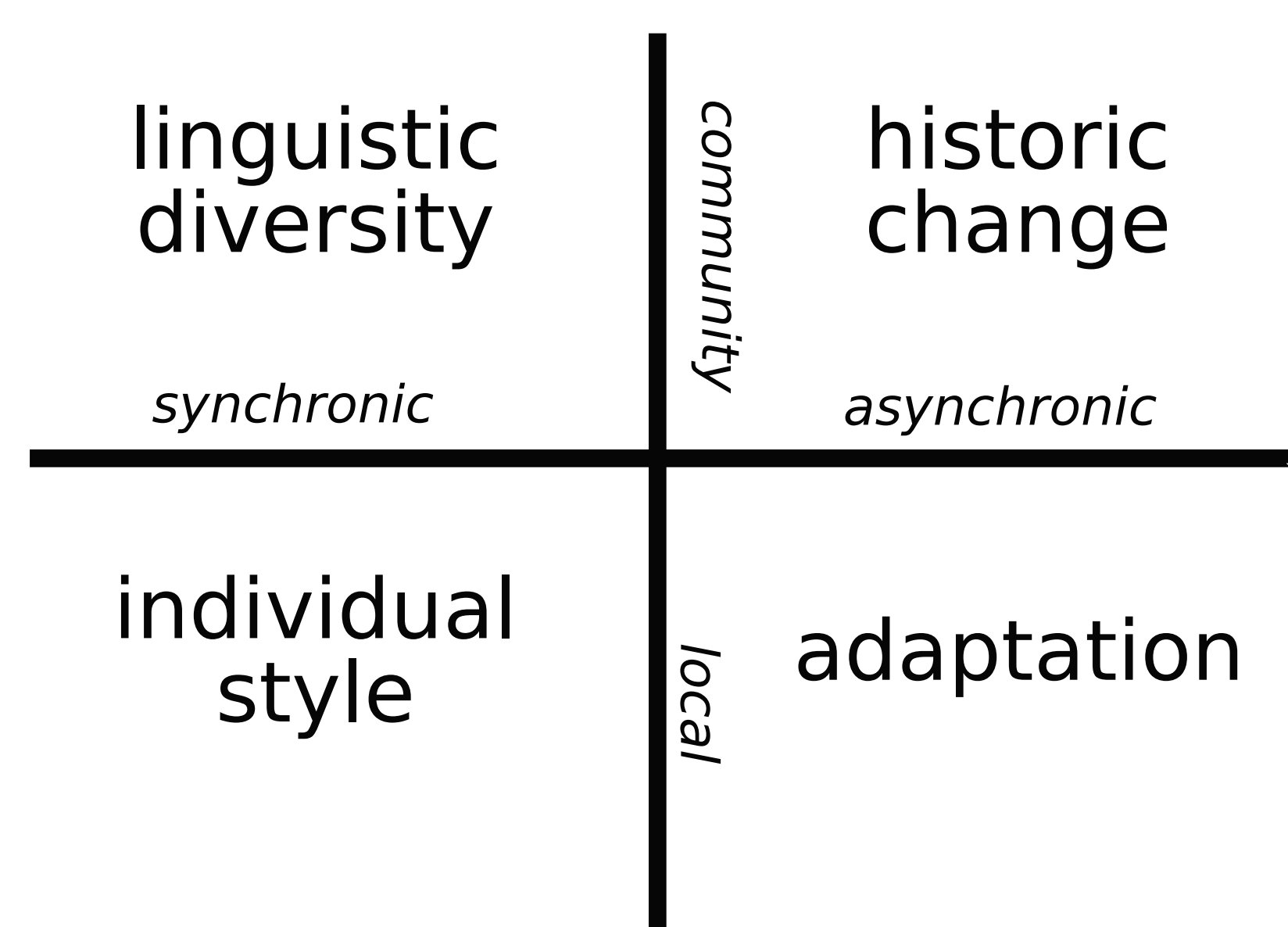
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Semantic Change

Sources of Semantic Variation

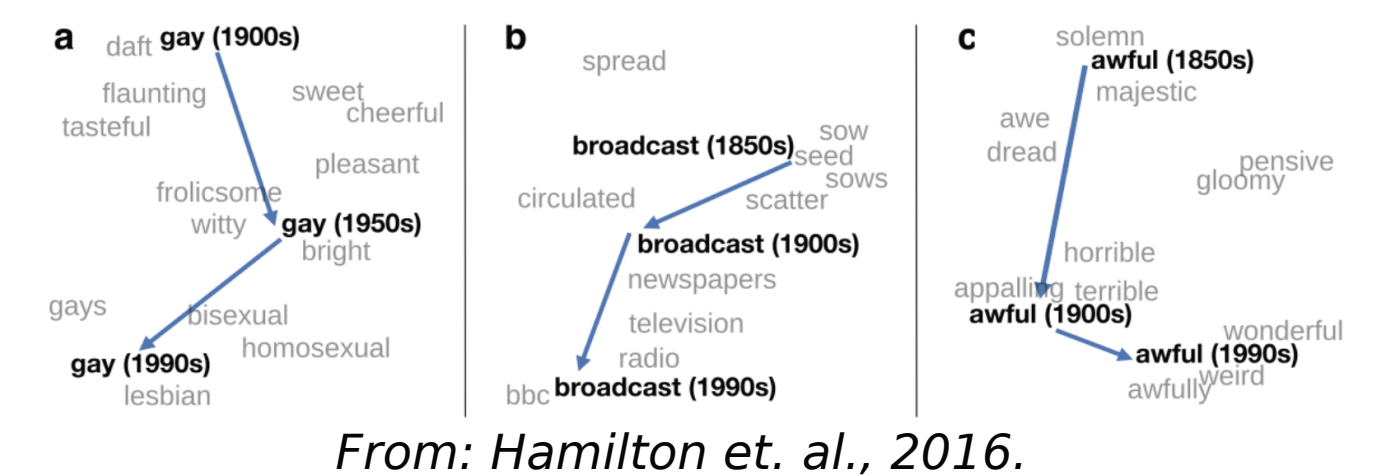
Successful communication requires lexico-semantic overlap.

Nevertheless, a given expression often has different meanings across uses.



Historic Semantic Change

Distributional semantics characterizes the meaning of words based on the contexts in which they appear. The most popular distributional models assign a vector to each word, where the spacial relationship between vectors models the semantic relationship between the words.



From: Hamilton et al., 2016.

In distributional models, the semantic distance between two words is estimated by the cosine distance between the vectors representing their meaning (Turney and Pantel, 2010).

In general, it is not possible to compare word vectors trained on different bodies of text due to random differences in model initialization.

However, methods such as orthogonal Procrustes can be used to align semantic vector spaces (e.g., Hamilton et al., 2016). By comparing representations of the same word across time, it is possible to detect semantic change.

Semantic adaptation

Over the course of a dialogue, participants collaborate to establish and refine a *common ground* that supports further communication (Clark and Schaefer, 1989).

Common ground can have either a **perceptual basis** (e.g., supported by a joint activity), or a **communal basis** (supported by common membership in some community).

In a dialogue, the common ground includes dialogue-specific conventions about the meaning of new and existing lexical items (Brennan and Clark, 1996). New semantics can be coordinated *implicitly* (by listener acceptance) or *explicitly* (e.g. through clarification and repair) (Larsson, 2007; Mills and Healey, 2008).

Example (Brennan and Clark, 1996)

A: A docksider.
B: A what?
A: Um.
B: Is that a kind of dog?
A: No, it's a kind of um leather shoe, kinda preppy pennyloafer.
B: Okay okay got it.

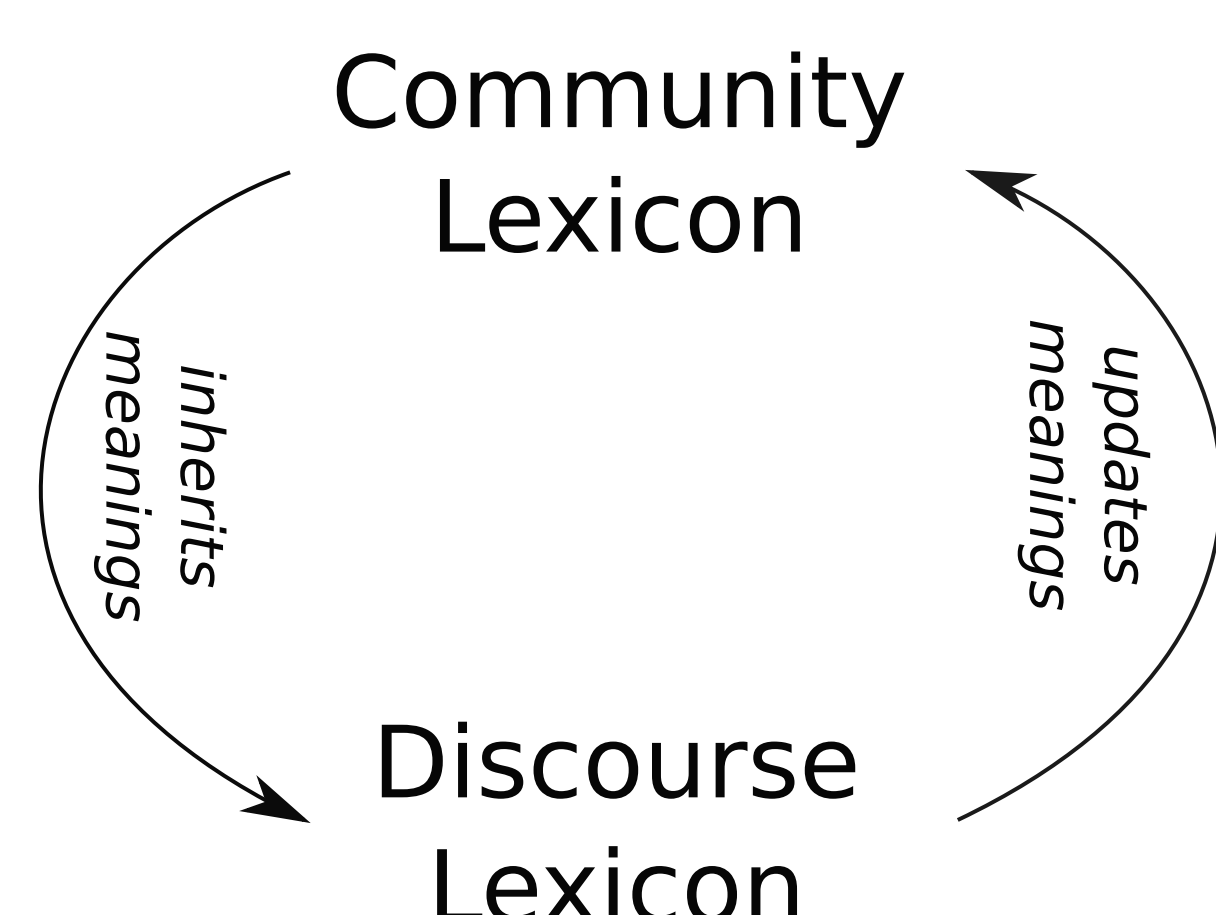
Once A and B have established a reliable way to refer to the shoe, they stick with the convention *pennyloafer*, even though A's preferred term at the start of the discourse was *docksider*. Semantic accommodation of this kind is an example of semantic adaptation.

Model

To investigate the relationship between semantic adaptation (change during a dialogue) and historic semantic change, we begin with a hierarchical lexical model (Noble, 2015) that includes both a community-level lexicon and a discourse-level lexicon.

The community lexicon is grounded with a communal basis. For a given set of agents, the **community lexicon** is the one everyone has access to, based on joint membership in some community. The **discourse lexicon** is initialized at the start of a dialogue, inheriting meanings from the most relevant (in the present context) community lexicon that is shared by all participants.

It's important to note that although both the community lexicon and the discourse lexicon are taken as common ground by the participants, every speaker has their own representation of each, and discrepancies are a key trigger of semantic adaptation.



Semantic change

The discourse lexicon reflects changes and refinements to the meaning of words made through the course of the dialogue (semantic adaptation). Evidence suggests that, within a dialogue, speakers persist in using adapted semantics, rather than falling back on community-level resources (Brennan and Clark, 1996)

Under the right conditions, changes made through semantic adaptation may persist in future dialogues, propagating up to the community lexicon.

Hypothesis

Based on this model, we expect that intra-dialogue semantic change (in aggregate) predicts semantic change at the community level.

In particular, we predict that, for words that experience community-level change, subsequent uses (in aggregate) are closer to the future state than the first-use (in a dialogue) semantics.

Experiments

To compare vectors across time periods and between dialogue partitions, we use orthogonal Procrustes, as described by Hamilton et al. (2016). Additionally, for each time period, we distinguish between subsequent and first-use semantics as follows:

$$\mathbf{w}^0 \leftarrow \begin{pmatrix} \mathbf{w} & \mathbf{w} & \dots & \mathbf{w} \\ \mathbf{w} & \mathbf{w} & \dots & \mathbf{w} \\ \mathbf{w} & \mathbf{w} & \dots & \mathbf{w} \end{pmatrix} \rightarrow \mathbf{w}^i < 0$$

Hypothesis 1: Semantic adaptation of a word predicts historic change.

$$\text{cosdist}(\mathbf{w}_t^{i>0}, \mathbf{w}_t^0) \text{ is correlated with } \text{cosdist}(\mathbf{w}_t, \mathbf{w}_{t+1}^0)$$

Hypothesis 2: in general the direction of intra-dialogue adaptation indicates the direction of semantic change.

$$\text{cosdist}(\mathbf{w}_t^{i>0}, \mathbf{w}_{t+1}^0) < \text{cosdist}(\mathbf{w}_t^0, \mathbf{w}_{t+1}^0)$$

References

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