Approximating the semantic space: word embedding techniques in psychiatric speech analysis

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Measuring 'coherence': Where do we stand?

- LLMs provide approximations of meaning that allow studying alterations of the structure of the semantic space in psychosis and their cognitive basis.
- Recent research provides cross-linguistic evidence of a pattern of increased semantic similarity jointly with increased perplexity [3], suggesting different patterns of navigating the semantic space at lexical-conceptual and grammatical levels.
- This study aimed to improve interpretability, generalizability and specificity of this pattern through a contrastive methodological scrutiny of different word embedding techniques and both static and dynamic semantic variables.

Methods

- **Sample**: 129 German speakers: 43 SSD, 43 MDD, 44 healthy controls (HC), with speech samples collected from four pictures descriptions (3 minutes each, Thematic Apperception Test (TAT) ([4]).
- **Variables**:
  - **Word and sentence embeddings**: fastText ([2]) and BERT ([1]) for words, SentenceTransformers ([4]) for sentences.
  - **Sentence embedding centroids**: Averaged dimensions to distinguish groups/pictures.
  - **Semantic similarity**: mean, max, min, slope sign change (SSC), mean crossing and autocorrelation of pairs of semantic units derived from the wave function of semantic similarity values.
  - **Displacement**: Sum of Euclidean distances, which unlike cosine similarities do not collapse high-dimensional spaces, preserve geometrical relationships.
  - **Convex hull and dimensionality reduction**: Samples as hyper-polyhedrons from embeddings; volume and area measured after t-Distributed Stochastic Neighbor Embedding (t-SNE) ([5]).

Statistical analysis:

- **k-nearest neighbors** (kNN) applied post-dimensionality reduction using t-SNE for picture and group classification.
- **Mixed-effects models** for group semantic differences, controlling for picture and speech sample length.

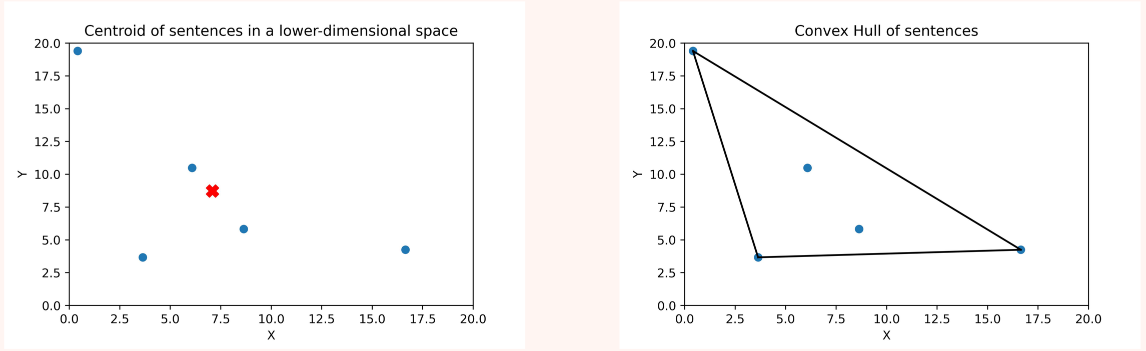

Figure 1. Centroid embedding of sentences (left), and convex hull (right).

Results: 1

- **Baseline content analysis** (Fig. 2): Groups navigate the same semantic space – implying that they may navigate in different ways.
- **Picture effect**: Different pictures have a significant effect on semantic similarity variables.

Results: 2

- **Static and dynamic semantic similarity variables** (Table 1): Lack of significant differences between groups in the mean. A significance increase in maximum semantic similarity for the BERT model, together with less slope sign changes in the time series of distances in SSD point in the direction of a shrinking semantic space. Traces of this are also found in MDD, with higher autocorrelation and less average crossing.
- **Displacement** (Table 2): Larger displacement in SSD relative to HC, despite unchanged centroids and mean semantic similarities.
- **Dispersion** (Table 3): Larger dispersion of sentence embeddings in MDD relative to HC.
- **Convex hull volume** (Table 4): Significant increase in the volume of the convex hull in SSD compared to HC.

Classification of text centroids

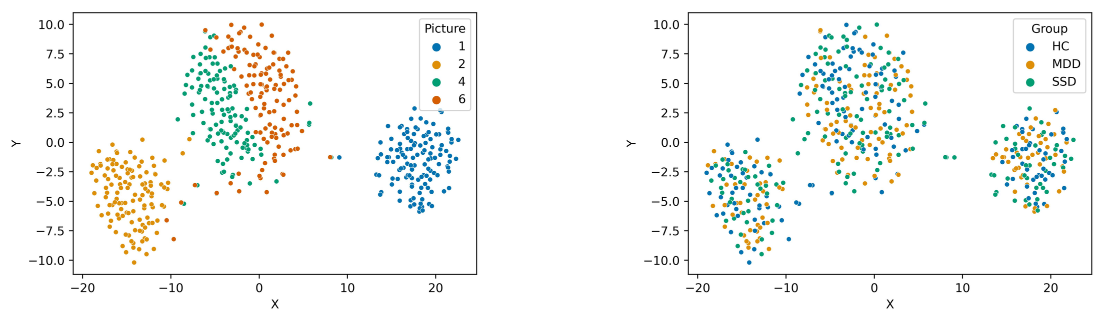

Figure 2. Classification of text centroids from sentence embeddings in 2D. By picture (left), and group (right).

Static and dynamic semantic variables

Table 1. Summary of groups effects on semantic similarity variables.

	FastText		BERT	
Variable	**MDD**	**SSD**	**MDD**	**SSD**
mean semsim	n.s.	n.s.	n.s.	n.s.
max semsim	n.s.	n.s.	n.s.	Positive
min semsim	n.s.	n.s.	n.s.	n.s.
average ssc	n.s.	n.s.	n.s.	Negative
average crossing	Negative	n.s.	n.s.	n.s.
autocorrelation	Positive	n.s.	n.s.	n.s.

Displacement

Table 2. Summary of Mixed Linear Model Regression results for Cumulative Euclidean distance

	Coefficient	Std. Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	-16.469	4.813	-3.422	0.001	-25.902	7.036
SSD	18.649	4.516	4.516	0.000	9.798	27.501
Content words	1.199	0.036	33.655	0.000	1.129	1.268
Av sentence length	-0.407	0.130	-3.139	0.002	-0.661	-0.153

Dispersion

Table 3. Summary of Mixed Linear Model Regression results for dispersion

	Coefficient	Std. Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	0.707	0.010	68.545	0.000	0.687	0.728
MDD	0.015	0.005	2.817	0.005	0.005	0.026
Picture 2	-0.022	0.006	-3.703	0.000	-0.033	-0.010
Picture 4	0.013	0.006	2.147	0.032	0.001	0.024
N of sentences	-0.003	0.000	-9.423	0.000	-0.003	-0.002
Av sentence length	-0.001	0.000	-1.782	0.075	-0.001	0.000

Note: In this table we only include significative independent variables

Volume of convex hull

Table 4. Summary of Mixed Linear Model Regression results for volume

	Coefficient	Std. Error	z	$P > \|z\|$	[0.025	0.975]
Intercept	0.153	0.664	0.230	0.818	-1.148	1.453
MDD	0.433	0.860	0.503	0.615	-1.253	2.118
SSD	1.737	0.867	2.004	0.045	0.038	3.436
above median	3.018	0.537	5.623	0.000	1.966	4.070

Discussion

- Controlling for picture effects and sample and sentence length, reveals that despite a shared semantic space (centroids), and lack of group differences in the mean semantic distances, navigational patterns (trajectories) across this space differ in both MDD and SDD.
- These changes are consistent with a more restricted ('shrinking') semantic space.
- SDD exclusively sensitive to BERT embeddings while MDD only to fastText suggest differential patterns in contextual-grammatical vs. lexical-conceptual semantic levels in these groups.

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