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Mapping perceptual spaces of objects and low-level features

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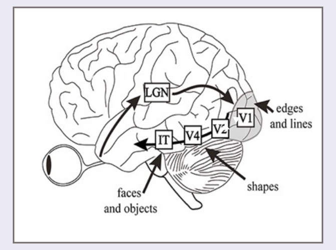
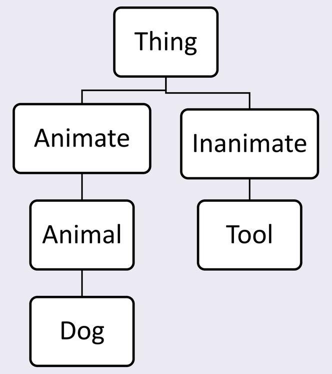
INTRODUCTION

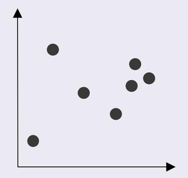
As signals pass through the network of visual areas, purely visual information is transformed into semantic information.



QUESTION: How does the representation of **early-stage, sensory** information, e.g., visual texture, differ from **semantic** representations?



PLAN: To study the mental representations of five distinct stimulus domains varying in their semantic content, using the framework of perceptual spaces.[1]



Our working definition of a *perceptual space* is a mental representation in which points in a space denote stimuli and distances denote perceived dissimilarity.

***HYPOTHESIS:** Representing semantic information uses a different geometry from representing low-level features.*

METHODS

Using five stimulus domains varying in their level of semantic content (examples below), we ran parallel psychophysical experiments, with 1-3 subjects. We assessed the geometry of the representation of each domain by asking subjects to make similarity judgments. The stimuli were all derived from a set of 37 animals.

Stimulus Domains

1. **Texture Domain:** fully scrambled textures
2. **Texture-like Intermediate Domain:** texturized images of these animals [2]
3. **Image-like Intermediate Domain:** slightly pixelated images of animals [2]
4. **Image Domain:** 37 unique recognizable images of the animals
5. **Word domain:** the names of 37 familiar animals (from WordNet)

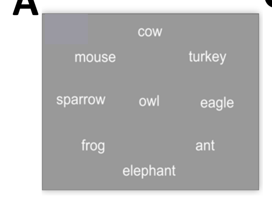
Experimental Paradigm: In a typical experiment, a series of trials are presented in which 8 stimuli from one domain are shown around a central reference. The task is to click stimuli in the surround in order of similarity to the reference. Subjects cannot change their judgments; once clicked, a stimulus grays out, indicating it is no longer a valid option. There are 222 unique trials, in which each stimulus serves as the central item in 6 trials and is paired with each of the other 36 items at least once. These 222 unique trials are each repeated 5 times in the course of 10 sessions of 111 trials each.

Data Collection Details: ***Subjects:*** 3F; VA: 20/20. ***Image stimuli:*** Image size: 2.25 deg, Check size for texture and texture-like stimuli: approximately 13.3 arcmin, Diameter of the display: 12.2 deg. Data were collected via Zoom by giving subjects remote control of a laptop screen.

RESULTS: Choice Probabilities

Similarity judgments can be broken down into choice probabilities, i.e., the proportion of times that a subject chooses one stimulus before another, in the same trial. (Fig. **C**). The distribution of choice probabilities is consistent across 3 subjects. Heatmaps (Fig. **D**) show the results from the **word** domain.

A



B

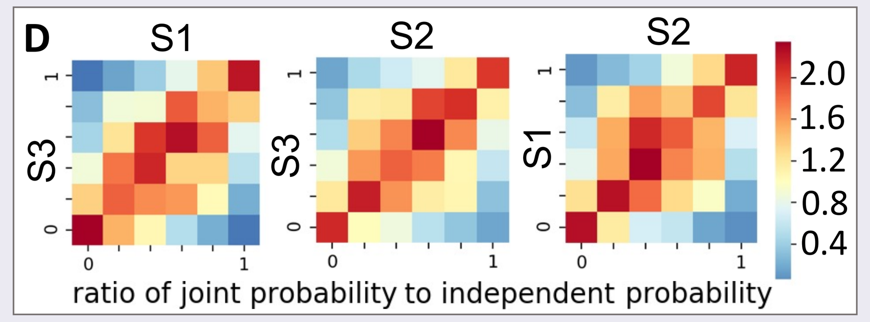
1. eagle, sparrow, turkey, frog, mouse, cow, elephant, ant
2. eagle, sparrow, turkey, mouse, frog, cow, elephant, ant
3. eagle, sparrow, turkey, cow, elephant, frog, mouse, ant
4. eagle, sparrow, turkey, frog, cow, mouse, elephant, ant
5. eagle, sparrow, turkey, mouse, frog, cow, elephant, ant

C

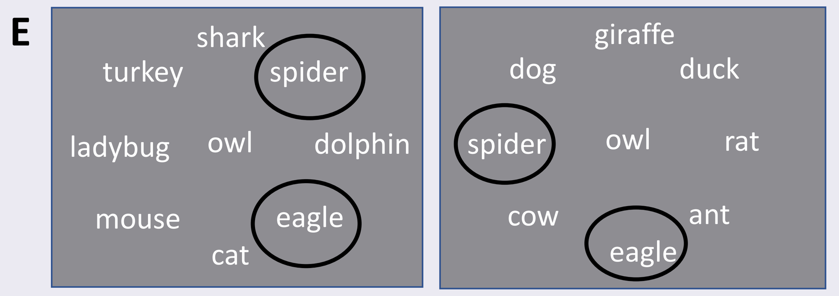
Comparison	Frequency
d(owl, cow) < d(owl, frog)	1/5
d(owl, mouse) < d(owl, elephant)	4/5
d(owl, eagle) < d(owl, turkey)	5/5

We also investigated the role of context on similarity judgments. Our paradigm included some trials in which the central reference appeared with a pair of stimuli in the surround, in two different groupings (Fig. **E**).

D

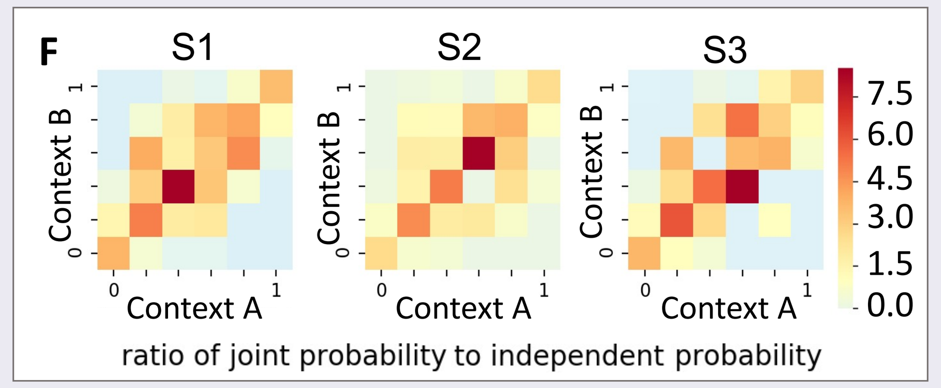


E



We found that, across such trials, the choice probabilities of judgments were highly consistent across contexts. As indicated by the diagonal in Fig. **F**, if a subject thought 'eagle' was more like 'owl' than 'spider' was to 'owl', in one context, it tended to be the case in the second context too.

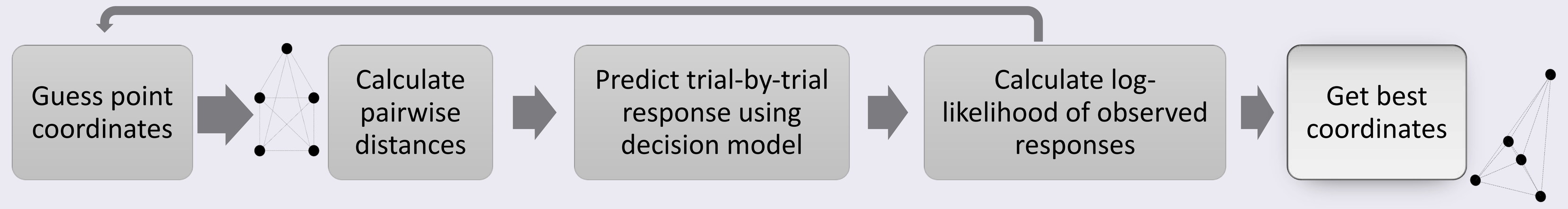
F



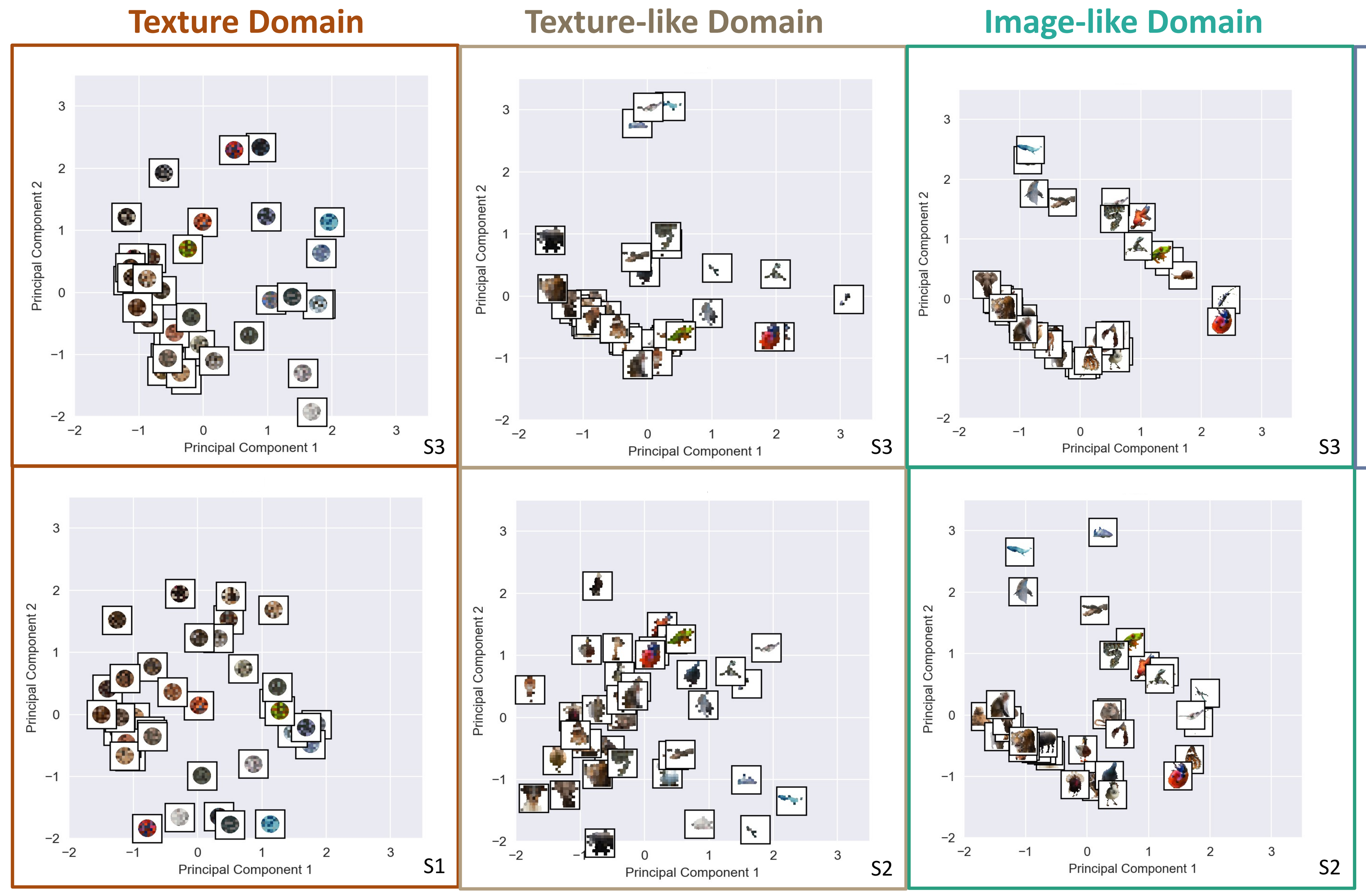
After the above processing, we use similarity judgments to derive a model for the geometry of each perceptual space, as outlined below.

MODELING THE PERCEPTUAL SPACES

We derived Euclidean models of perceptual spaces of 2, 3, 4 and 5 dimensions using a maximum likelihood approach.



Decision Model: Subjects' decision-making in each trial was interpreted as a set of independent, binary choices of the form "Is the distance between the reference and s_1 less than that between the reference and s_2?" for all pairs of stimuli in the surround. We modeled these decisions as the comparison of two distances with additive Gaussian noise representing errors in estimation.



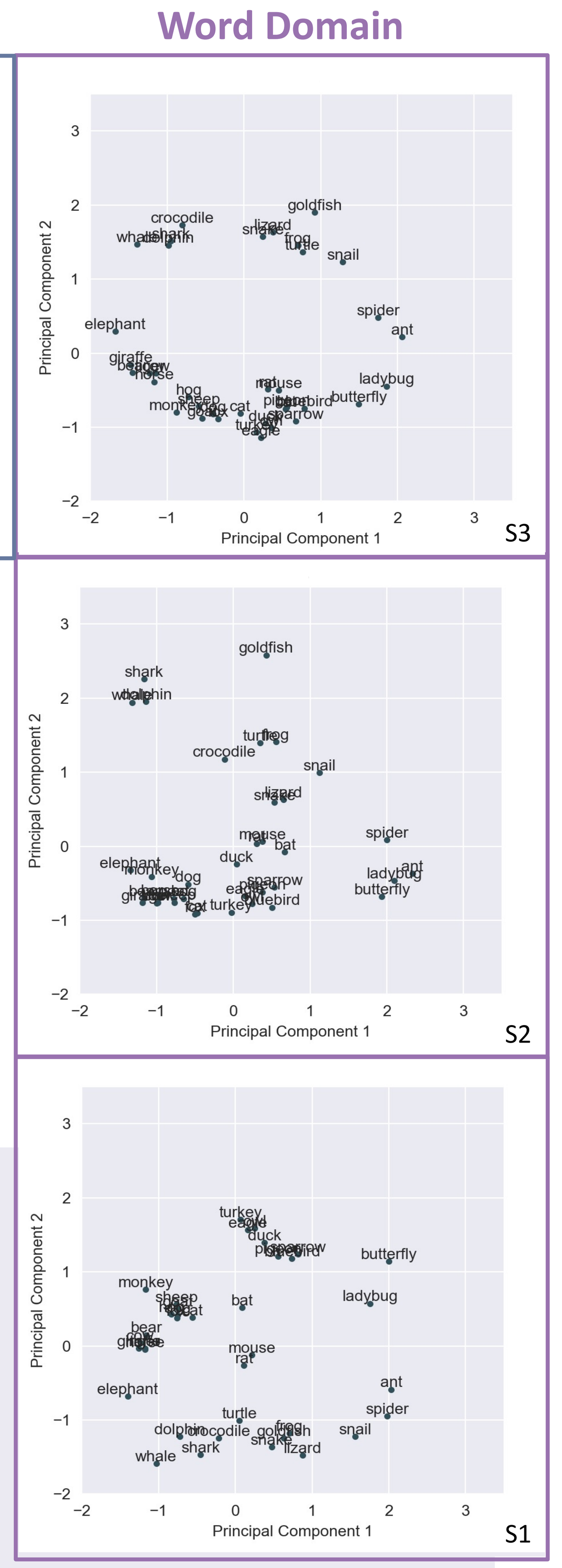
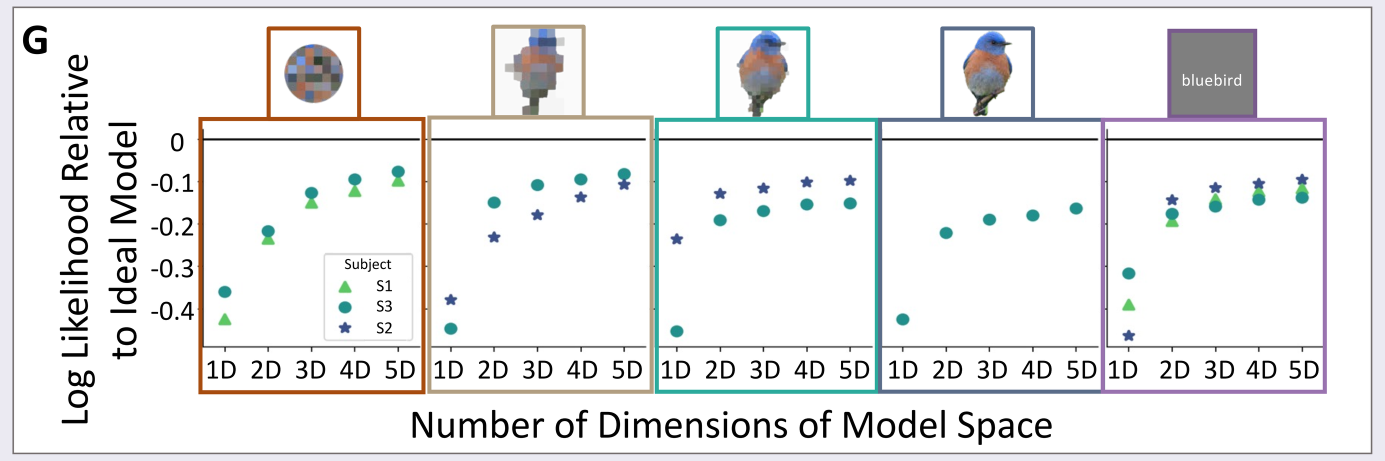


Figure H. *The projection of 5D coordinates onto the first two principal components, normalized by the variance along each component.*

RESULTS: Geometry of the Perceptual Space

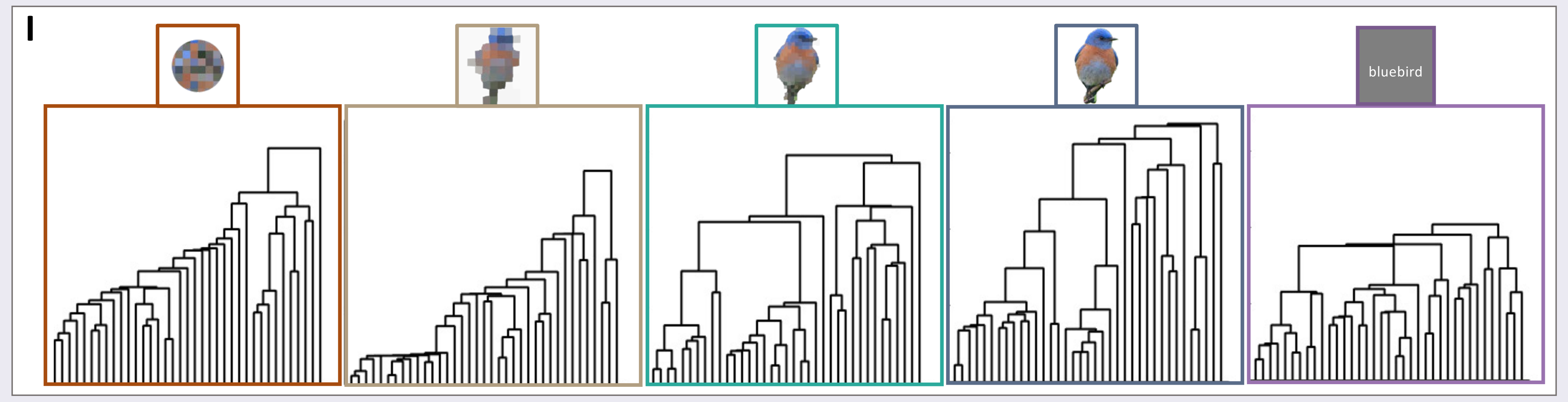
All domains appeared to require at least 5 dimensions to fully account for the judgments (Fig. **G**). However, projections into the first two dimensions revealed a systematic change in the way that the stimuli are distributed: in the more semantic domains, they tend to occupy the periphery of the space (Fig. **H**).

G

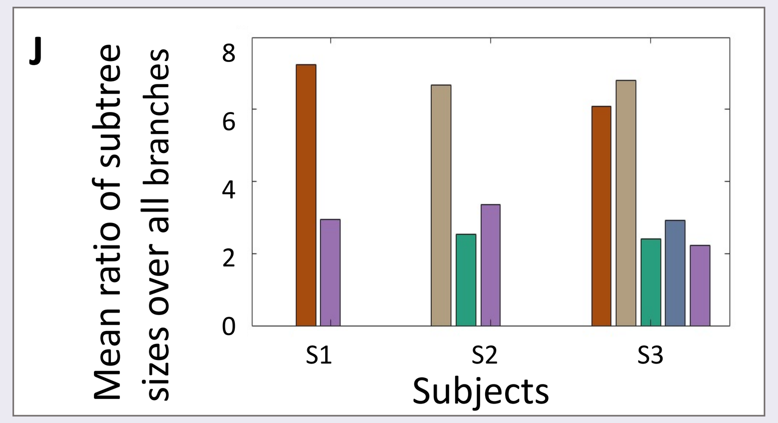


Hierarchical clustering revealed a second way in which the geometry of the representations differs: unlike in the **texture** and intermediate, **texture-like** domains, branches in the dendrograms were more balanced in the **word** trees (Fig. **J** – a lower mean ratio corresponds to balanced branches). This suggests semantic space has categorical structure. Examples of dendrograms in Fig. **I** (Subject 3) were derived from points obtained from the 5D model.

I



J



CONCLUSIONS

- A high-dimensional space is required to explain similarity judgments from all domains.
- However, the organization of these domains differs.
- Domains with semantic content correspond to a more balanced tree.

REFERENCES

1. Zaidi, Q., et al. (2013). *J Neurosci* **33**(45): 17597-602.
2. Achanta, R., et al. (2012). *IEEE Trans Pattern Anal Mach Intell*, **34**(11): 2274-82.

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