SentSpace: Large-Scale Benchmarking and Evaluation of Text using Cognitively Motivated Lexical, Syntactic, and Semantic Features

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What is SentSpace?

- ❖ SentSpace is a modular, open-source framework for streamlined evaluation of text.
- ❖ SentSpace characterizes textual input using cognitively motivated lexical, syntactic, and semantic features.
- ❖ Features are derived from psycholinguistic experiments, large-scale corpora, and theoretically motivated models of language processing.
- ❖ Core sentence features fall into two feature modules:
  - **Lexical module**
  - **Contextual module**
- ❖ SentSpace can be accessed from a web interface or a Python package.
- ❖ The modular design of SentSpace allows researchers to easily integrate their own feature computation into the pipeline while benefiting from a common framework for evaluation and visualization.
- ❖ SentSpace provides a broad set of cognitively motivated linguistic features for evaluation of text within natural language processing, cognitive science, and the social sciences.

What Can SentSpace be Used For?

❖ **Text Generation/Dialog Systems.** *How does text generated by artificial language models compare to that generated by humans?*

SentSpace features can be used to compare text generated by artificial systems and humans. Moreover, these features may be used to guide artificial systems to generate text that is more human-like and/or has certain desired properties.

❖ **Language Model Grounding and Interpretability.** *What psycholinguistic information do high-dimensional vector representations from pre-trained language models capture?*

SentSpace features allow for interpretation of high-dimensional vector representations from large pre-trained language models. SentSpace serves as a complementary resource that can provide grounding to these widely used high-dimensional representations.

❖ **Experimental Sciences.** *How naturalistic is a set of experimental materials?*

SentSpace can be used to evaluate the normativity of experimental stimuli in experimental sciences such as neuroscience, cognitive science, and linguistics.

❖ **Analyzing Human Utterances.** *How do utterances produced by different human populations differ from each other?*

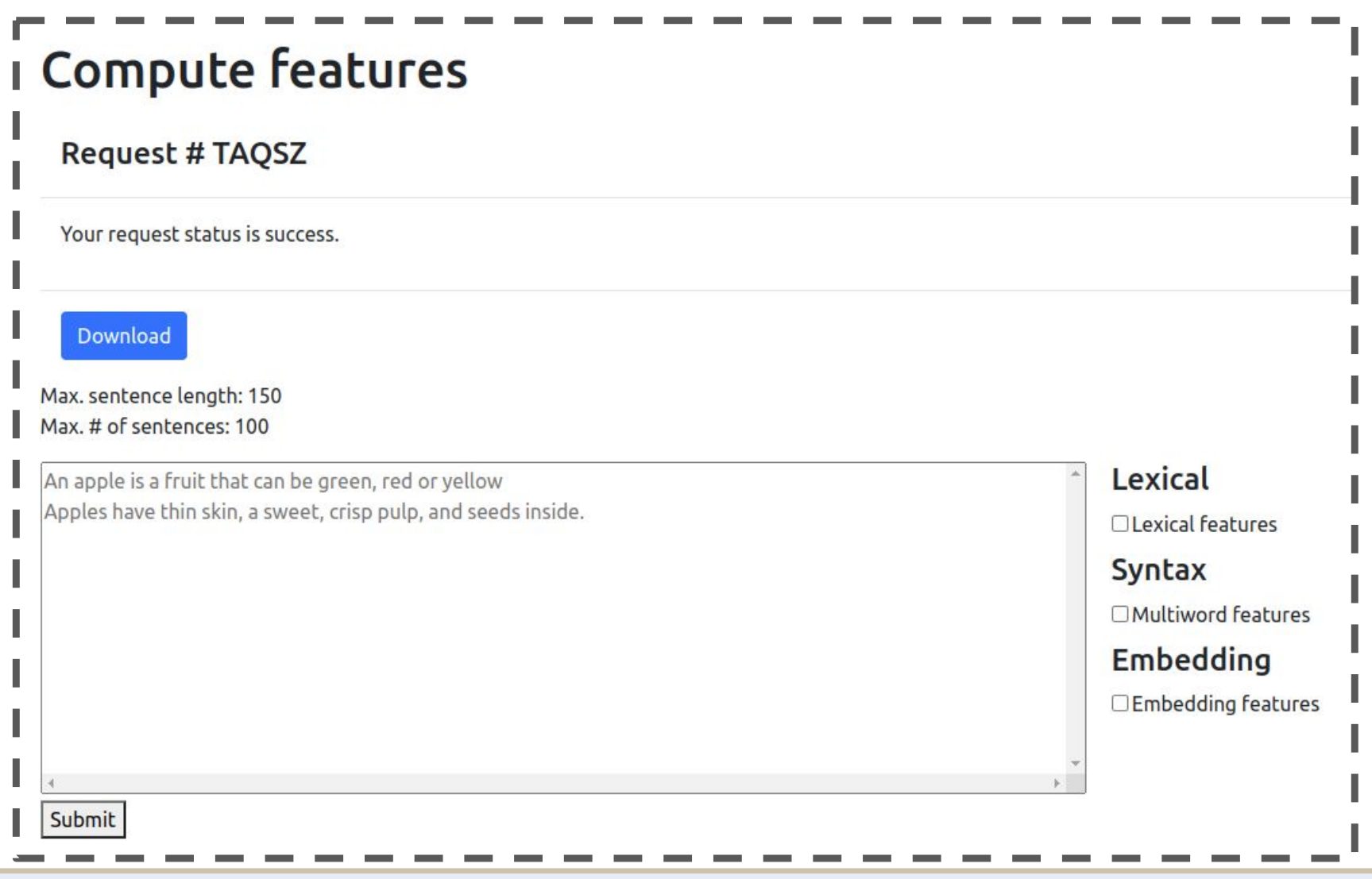
SentSpace can help meaningfully quantify divergence in utterances produced by different human populations such as e.g. neurotypical individuals and individuals with communication disorders.

Usage

1. Command-Line Interface (CLI)

```
python -m sentspace
  input  -lex 1   -syn 1
  -usermodule 1  -o output.csv
```

2. Hosted Frontend



Compute features

Request # TAQSZ

Your request status is success.

Download

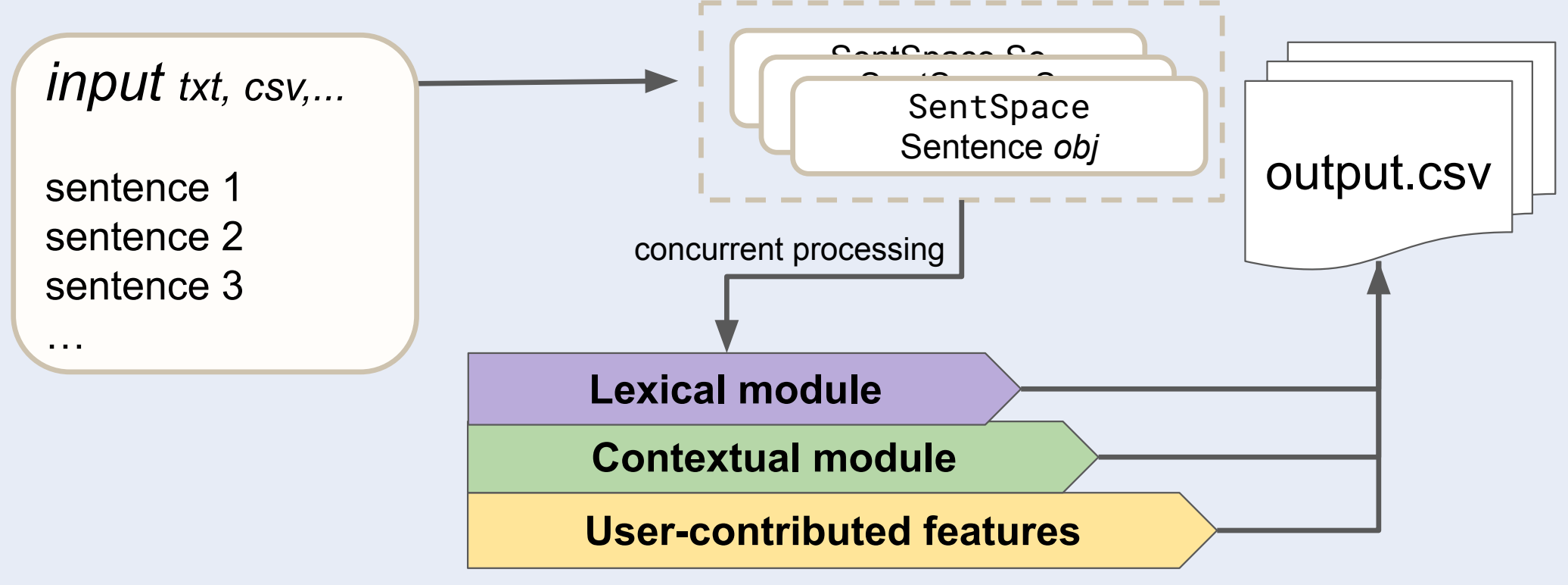
Max. sentence length: 150
Max. # of sentences: 100

An apple is a fruit that can be green, red or yellow
Apples have thin skin, a sweet, crisp pulp, and seeds inside.

Lexical
□ Lexical features
Syntax
□ Multiword features
Embedding
□ Embedding features

Submit

Data Flow



SentSpace Features

$$f(\text{sentence}) \mapsto \mathbb{R}^n$$

Where $\mathbb{R}^n$ can be any feature or representation which we organize into two main modules based on the nature of the sentence characterization: *Lexical* & *Contextual*

Lexical module

- ❖ Age of Acquisition (Kuperman et al., 2012)
- ❖ Arousal (Mohammad, 2018)
- ❖ Body-Object Interaction (Pexman et al., 2019)
- ❖ Concreteness (Brysbaert et al., 2014)
- ❖ Contextual Diversity (SUBTLEXus: Brysbaert & New, 2009)
- ❖ Dominance (Mohammad, 2018)
- ❖ Imageability (Scott et al, 2019)
- ❖ Lexical Connectivity (Mak & Twitchell, 2020)
- ❖ Lexical Decision Latency (Balota et al., 2007)
- ❖ Lexical Frequency (SUBTLEXus: Brysbaert & New, 2009)
- ❖ Number of Morphemes (Morfessor: Virpioja et al., 2013)
- ❖ Orthographic Neighbor Frequency (Medler & Binder, 2005)
- ❖ Orthographic-Semantics Consistency (Marelli & Amenta, 2018)
- ❖ Polysemy (Miller, 1992)
- ❖ Prevalence (Brysbaert al., 2019)
- ❖ Sensorimotor norms (11 different norms) (Lynott et al., 2020)
- ❖ Socialness (Diveica et al., 2022)
- ❖ Valence (Mohammad, 2018)

Contextual module

- ❖ Dependency Locality Theory (DLT) (Gibson, 2000):
  - ➢ Various features that quantify storage and integration cost based on the dependency structure of the sentence.
- ❖ Left-corner features (Rasmussen & Schuler, 2018):
  - ➢ Various features derived from a left-corner parser such as center embedding depth and constituent lengths.
- ❖ N-gram surprisal (Piantadosi et al., 2011)
- ❖ Part of Speech ratios
  - ➢ Content word ratio, pronoun ratio.

Extending SentSpace

User-contributed features

Users can contribute custom features in two ways:

- ❖ Simple token-level norms or lookup-based features requiring no computation: use a packaging utility

```
python -m
sentspace.package_lexical
  input.csv   --word_column Word
--feature_column LDRT
   --feature_name
lexical_decision_latency
```

- ❖ Features requiring computation:
  - ➢ Create a module following SentSpace API
  - ➢ `get_features:= Callable[sentspace.Sentence, Dict]`

```
→ {
        index: …, token: …,
        sentence: …, feature_name: val,
        …
    }
```

PRs welcome

Acknowledgements & References

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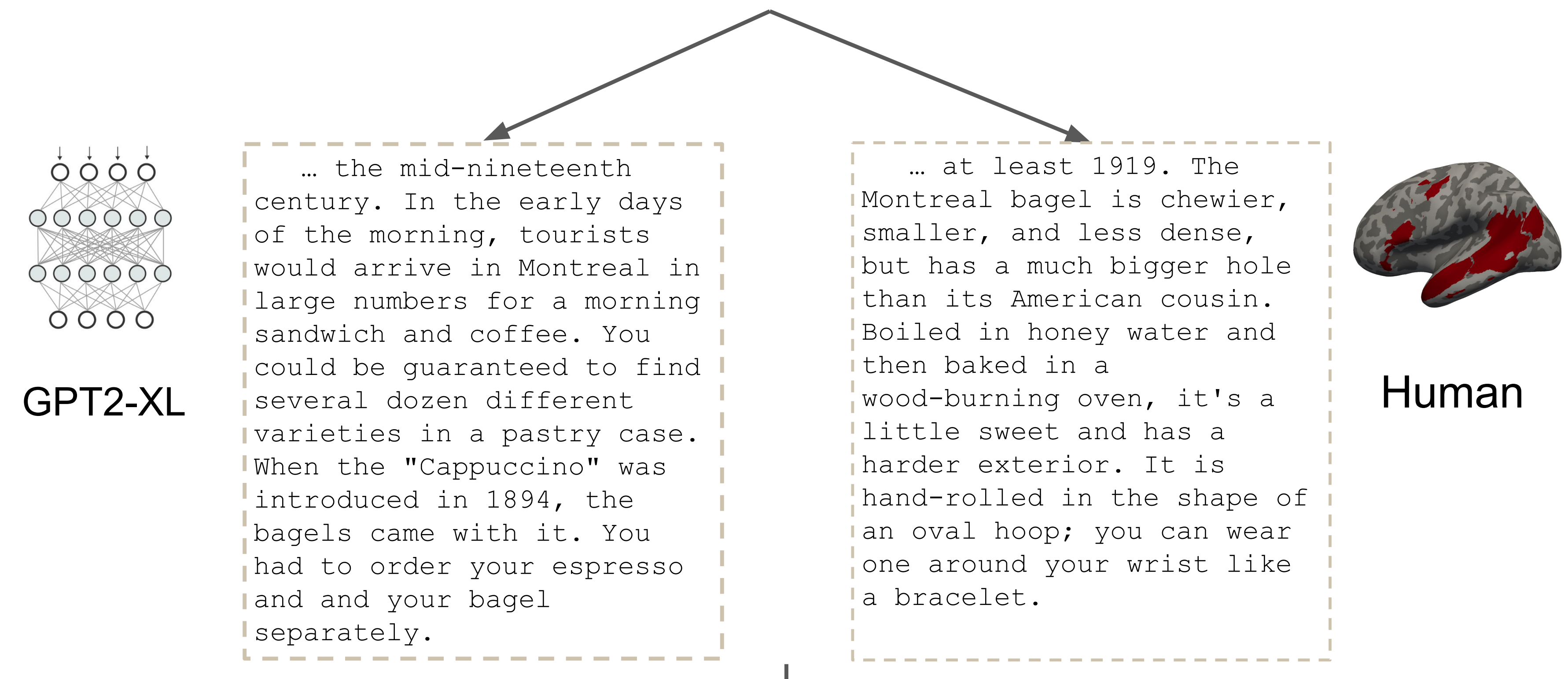
Brysbaert et al. (2014): *Beh Res Methods*, 46(3):904–911. **Brysbaert et al. (2019)**: *Beh Res Methods*, 51(2):467–479. **Brysbaert & New (2009)**: *Beh Res Methods*, 41(4):977–990. **Diveica et al. (2022)**: *Beh Res Methods*, 1-13. **Gibson (2000)**: *Image, Language, Brain*, 94-126. **Kuperman et al. (2012)**: *Beh Res Methods* 44(4):978-90. **Mak & Twitchell (2020)**: *Psych Bull Rev*, 27(5):1059–1069. **Marelli & Amenta (2018)**: *Beh Res Methods*, 50(4):1482–1495. **Medler & Binder (2005)**: *neuro.mcw.edu/mcword*. **Miller (1992)**: *Comm. ACM*, 38:39–41. **Mohammad (2018)**: *ACL 2018*. **Pexman et al. (2019)**: *Beh Res Methods*, *51*(2), 453-466. **Piantadosi et al. (2011)**: *PNAS*, 108(9):3526–3529. **Rasmussen & Schuler (2018)**: *Cog Sci*, 42 Suppl 4:1009-1042. **Virpioja et al. (2013)**: *Aalto University publication*, 978-952-60-5501-5.

Comparison Between Machine- and Human-Generated Text

Open source experiment code:
https://github.com/sentspace/NAACL-HLT-2022

- ❖ **Question:** Can we reveal quantitative differences between GPT2-XL-generated and human-generated text?
- ❖ **Approach:** Generate text using artificial language models (GPT2-XL) and humans:

Prompt:
"*Montreal has a unique bagel tradition that dates back to*"

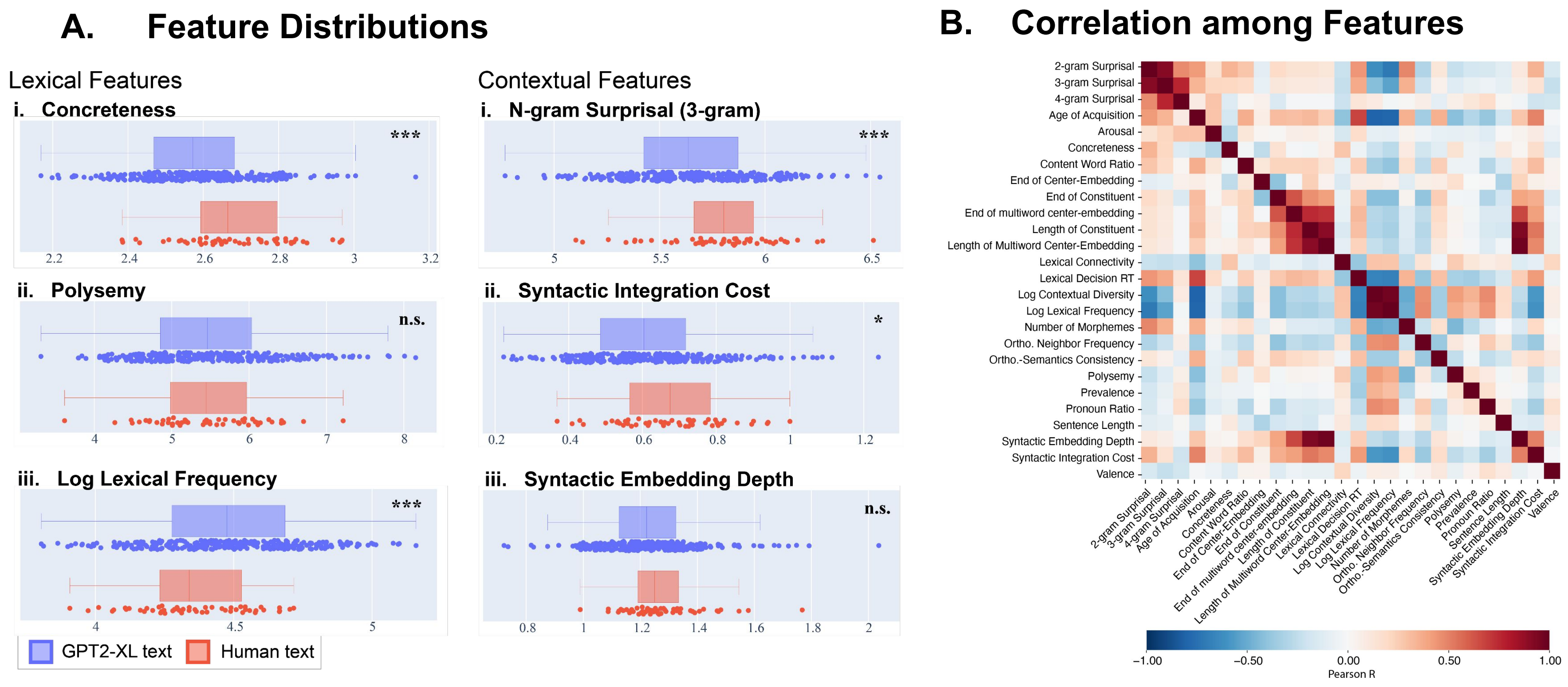


```
… the mid-nineteenth
century. In the early days
of the morning, tourists
would arrive in Montreal in
large numbers for a morning
sandwich and coffee. You
could be guaranteed to find
several dozen different
varieties in a pastry case.
When the "Cappuccino" was
introduced in 1894, the
bagels came with it. You
had to order your espresso
and and your bagel
separately.
```

```
… at least 1919. The
Montreal bagel is chewier,
smaller, and less dense,
but has a much bigger hole
than its American cousin.
Boiled in honey water and
then baked in a
wood-burning oven, it's a
little sweet and has a
harder exterior. It is
hand-rolled in the shape of
an oval hoop; you can wear
one around your wrist like
a bracelet.
```

52 unique 10-word prompts (GPT2-XL: 5 paragraphs per prompt; Human: 1 paragraph per prompt)

Obtain SentSpace features and compare GPT2-XL and humans


A. Feature Distributions

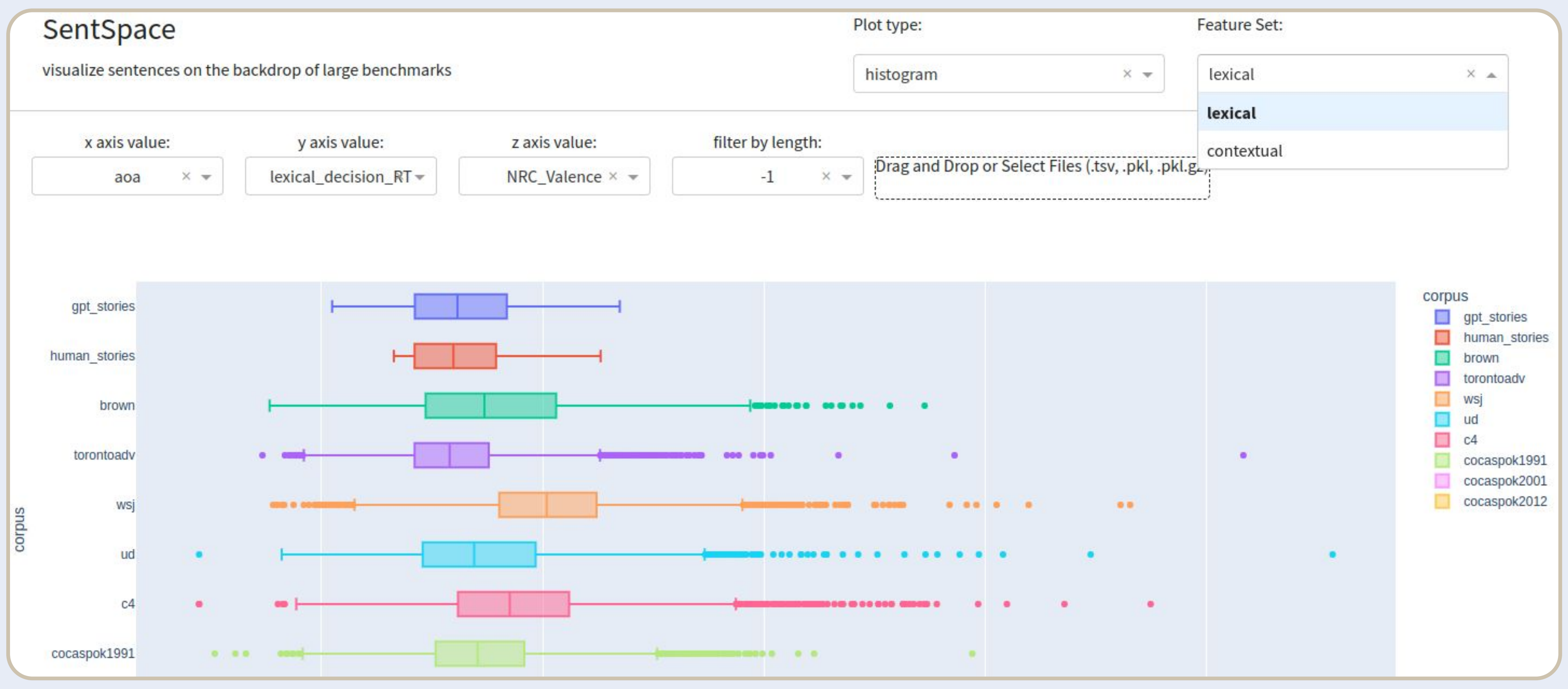
B. Correlation among Features

❖ **Conclusion:** GPT2-XL-generated text appears fluent at the surface level, but our features can reveal subtle differences between GPT2-XL and human-generated text: For instance, GPT2-XL produced less concrete sentences with shorter syntactic dependencies.

Visualization

Features can be visualized using the SentSpace visualization module (python -m sentspace.vis)

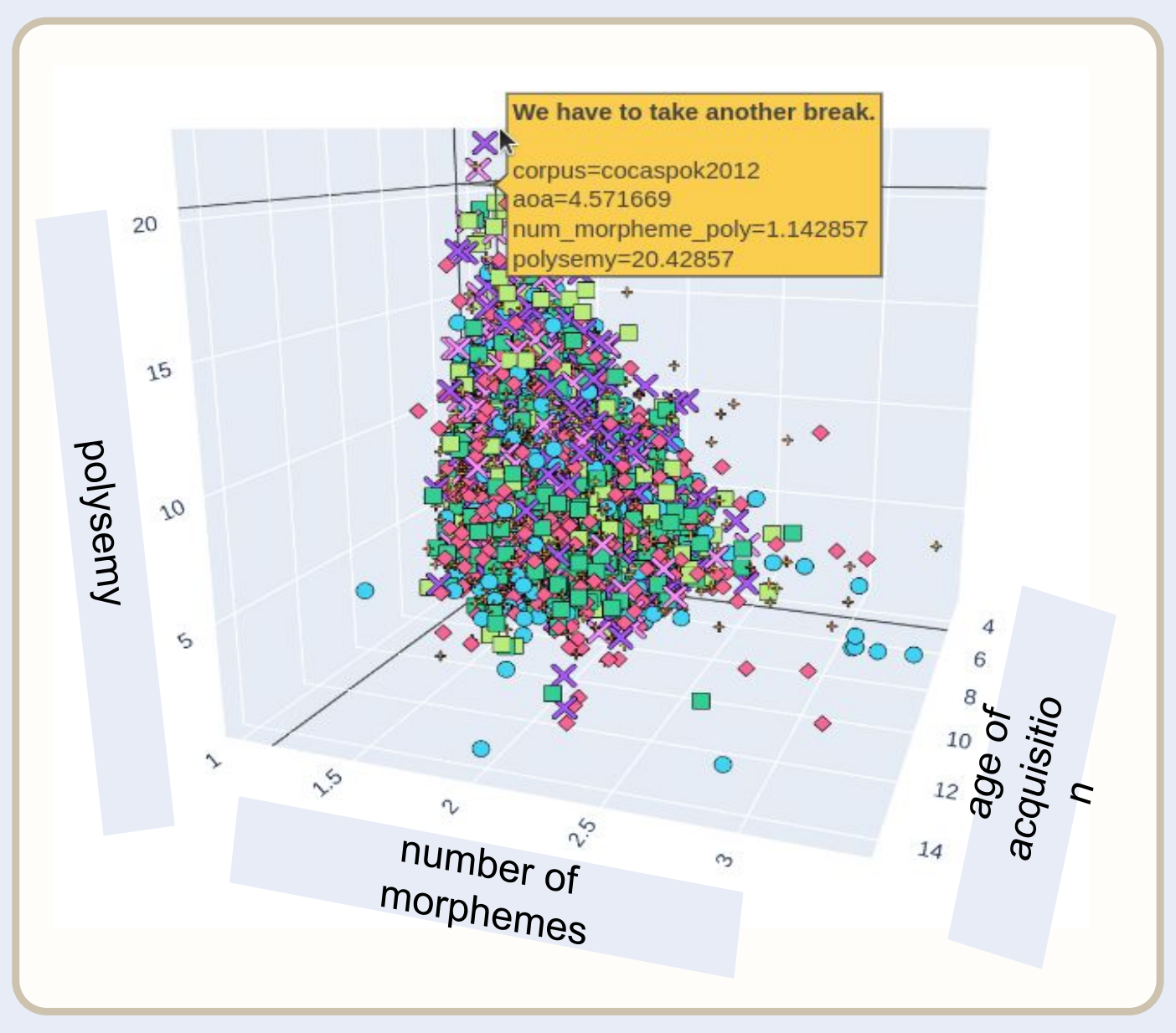
- ❖ Accepts features computed via the CLI or hosted frontend
- ❖ Displays mean, median, and outliers, as well as feature distributions



SentSpace
visualize sentences on the backdrop of large benchmarks

Plot type: histogram
Feature Set: lexical

x axis value: aoa
y axis value: lexical_decision_RT
z axis value: NRC_Valence
filter by length: -1



Hosted Frontend

sentspace.github.io/hosted

API Documentation

sentspace.github.io/sentspace