



A Neural Model for Predicting Dementia from Language

Weirui Kong (kongw@alumni.ubc.ca)¹ Hyeju Jang¹ Giuseppe Carenini¹ Thalia Field²

¹UBC Computer Science

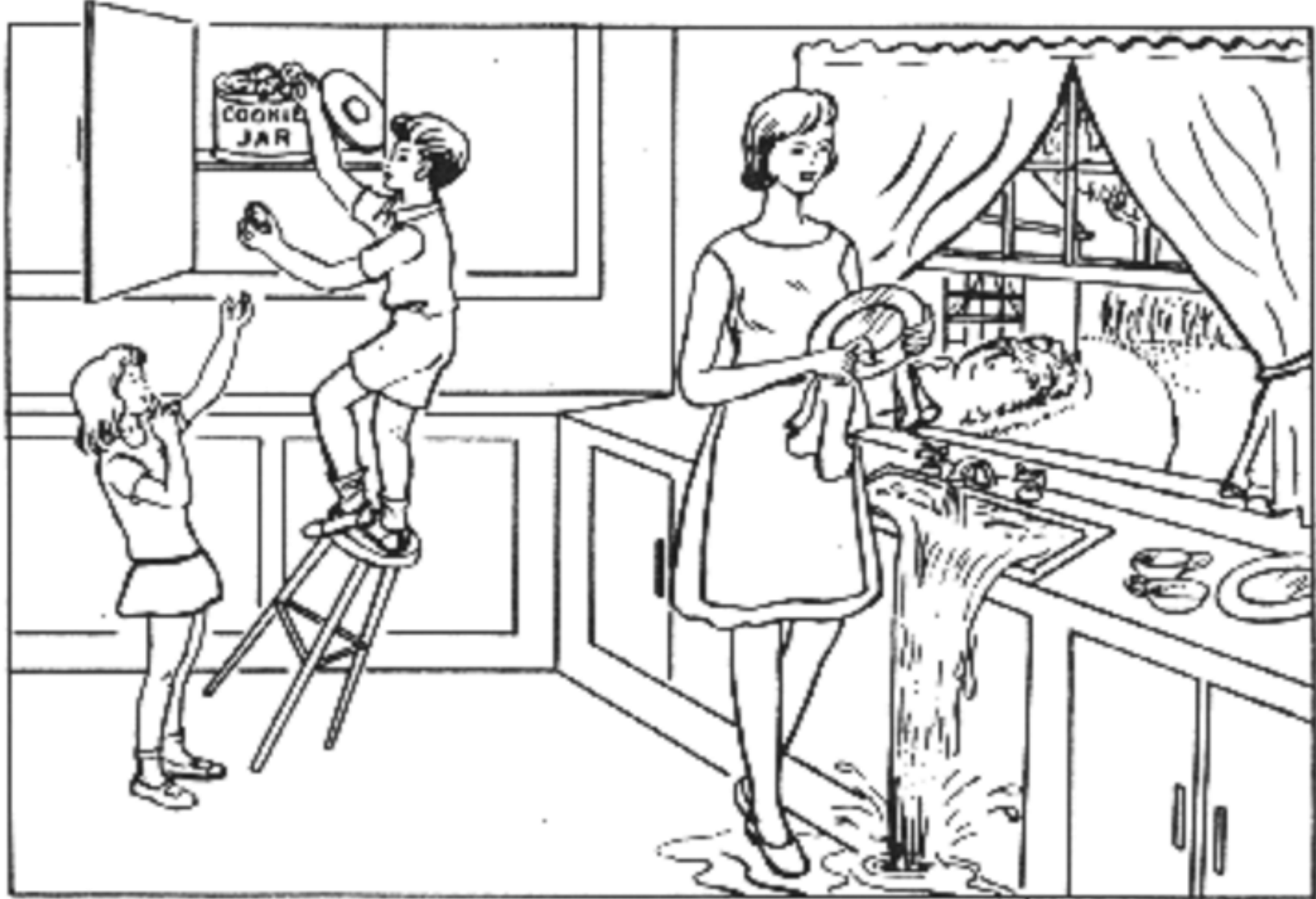
²UBC Faculty of Medicine

Dementia Prediction via Speech Analysis

- Current diagnosis of dementia: Clinical assessment incorporating history, exam and cognitive testing, supported by resource-intensive specialized tests (eg. neuroimaging, CSF biomarkers).
- Language changes can often occur early in the disease process. Subtle changes in language are observed a year or more before dementia is diagnosed [2].
- Target: Building ML and NLP based approaches for automated dementia prediction, which are non-invasive, inexpensive and easy to administer.

Dataset

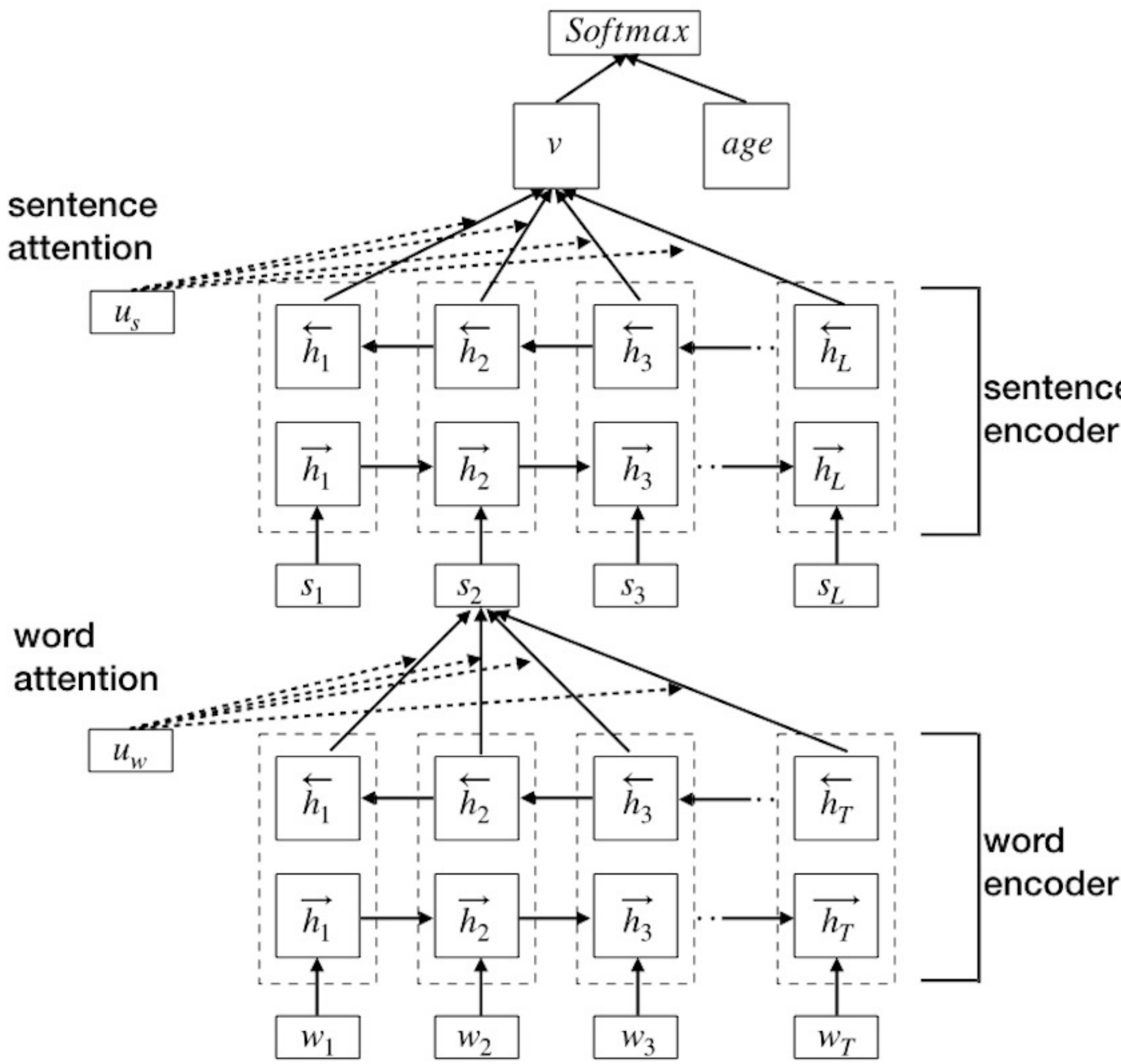
- DementiaBank: Audio recordings and manual transcripts of participants describing the Cookie Theft picture.
- 257 Alzheimer’s disease (AD) samples and 242 elderly healthy control samples.
- Human experts defined **information units** (e.g., mother, stool, overflowing), which capture the key concepts in the picture.



The Cookie Theft picture.

Hierarchical Attention Networks for Dementia Prediction

HAN: An end-to-end neural text classification model [4].



HAN for dementia prediction.

Traditional Baselines

Features used by traditional methods. **Info**: information unit features. **Spatial**: spatial neglect features. **Info** and **Spatial** features are task-specific: they are restricted to the Cookie Theft picture.

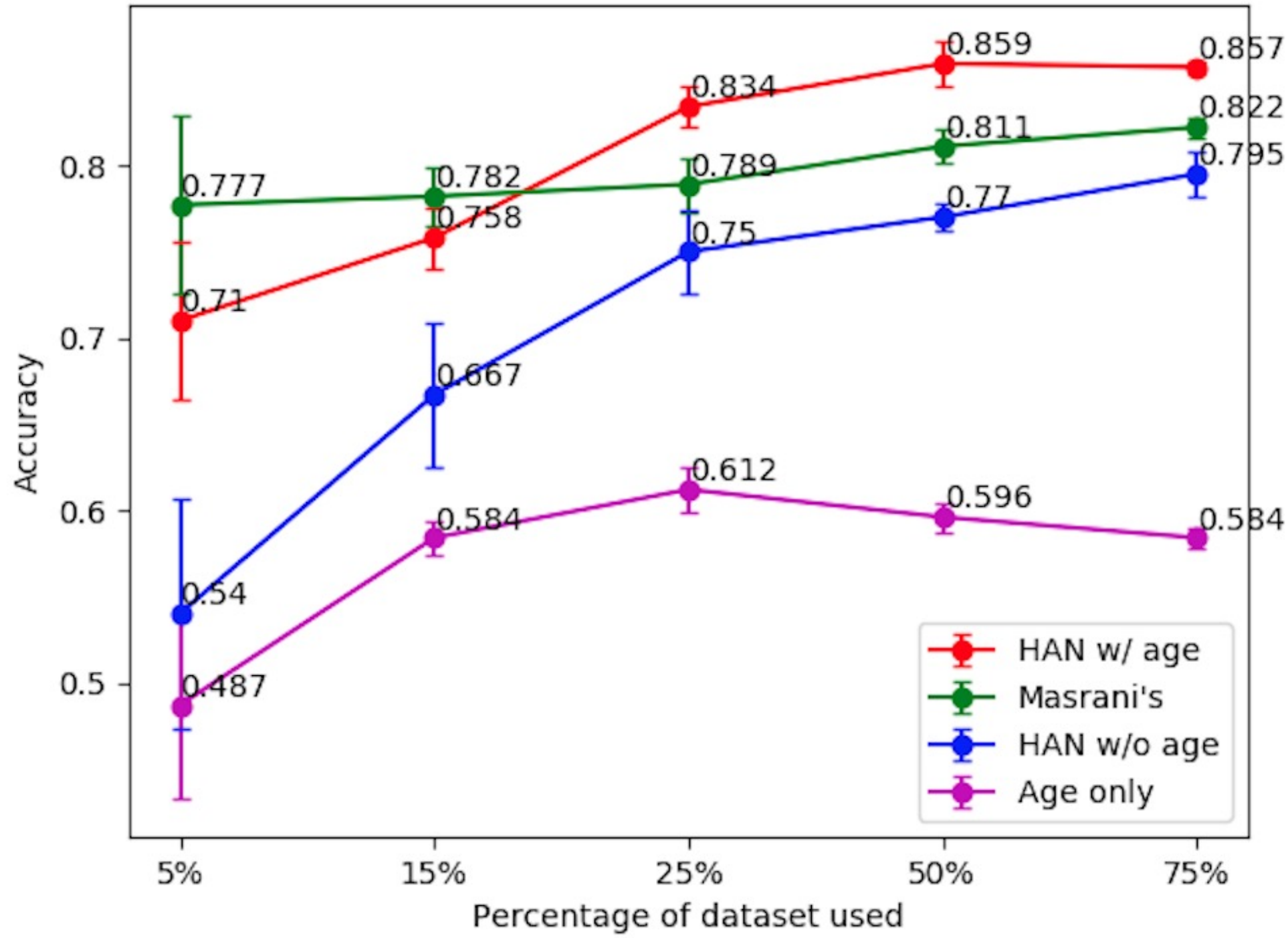
Dataset	Methods	Linguistic	Acoustic	Info	Spatial	Age
DementiaBank	Age only	×	×	×	×	✓
	Fraser et al. (2016) [1]	✓	✓	✓	×	×
	Masrani (2018)-B [3]	✓	✓	✓	×	✓
	Masrani (2018)-S [3]	✓	✓	✓	✓	✓
Dementia Blog	Masrani et al. (2017) [3]	✓	×	×	×	×

Experiment Result

Binary classification with 10-fold cross-validation. Note that results of Fraser’s model and Masrani’s model are from the original papers.

Model	Accuracy	Precision	Recall	F-score
Baseline (age only)	0.595	0.591	0.729	0.653
Fraser et al. (2016)	0.820	-	-	-
Masrani (2018)-B	0.822	-	-	0.824
Masrani (2018)-S	0.844	-	-	0.846
bi-GRU baseline	0.748	0.750	0.811	0.768
HAN	0.815	0.839	0.818	0.815
HAN-AGE	0.869	0.859	0.904	0.876

Effect of Dataset Size



Test accuracy by varying training data proportions.

Neural Attention Visualization

0.1371	well the girl is telling the boy to get the cookies down but do n't tell your mother .
0.1794	and the boy is also falling over off the stool .
0.1187	and the mother is letting the water run out of the sink .
0.1784	and she 's drying dishes .
0.091	i do n't quite get that but then ...
0.1479	uh she has water on the floor and and basically it 's kindof uh a distressing scene .
0.0887	everything 's going haywire .
0.0361	she needs to turn off the water .
0.0192	if she turned off the water she 'd be a hundred percent better off .

Visualization of word attention and sentence attention.

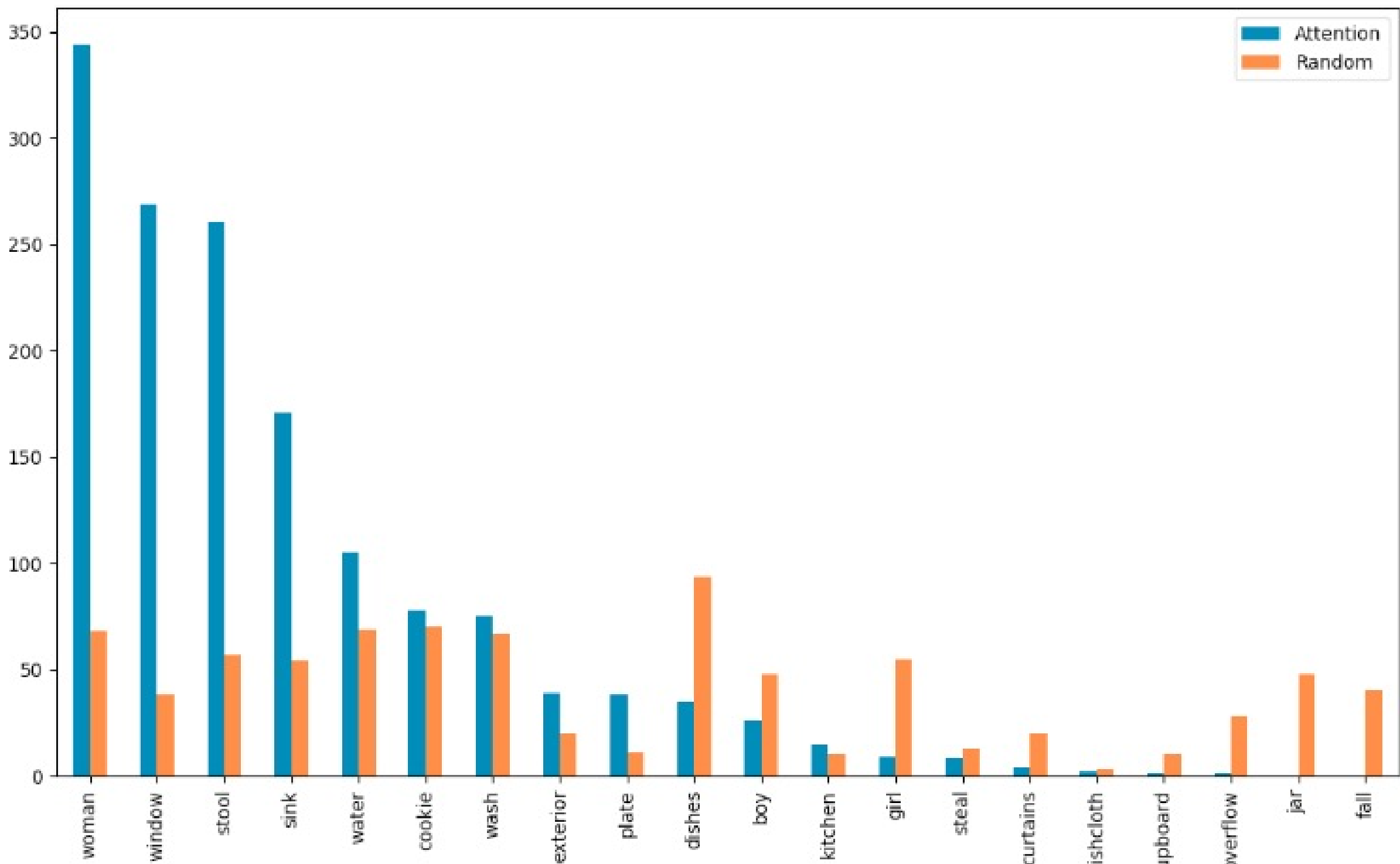
Neural Attention and Information Units

The χ^2 test shows that HAN appears to be able to capture similar information to the one specified by human experts.

Contingency table (numbers in parenthesis are expected values). $\chi^2 = 663, p < 0.00001$.

	Most emphasized	Not most emphasized	Total
Information unit	1481 (823)	7599 (8257)	9080
Non information unit	4889 (5547)	56270 (55612)	61159
Total	6370	63869	70239

Comparing attention frequency and random frequency of each info unit: The word attention attends more to a specific subset of information units.



Attention frequency vs. random frequency.

Conclusions and Future Work

- The HAN-AGE model not only achieves the state-of-the-art performance on the DementiaBank dataset, but shows a good prediction accuracy even when trained with a small portion of the available data.
- Visualization and statistical analysis reveal that the attention mechanism of the model manages to capture similar key concepts as the info units specified by human experts.
- The model using no task-specific feature could be easily generalized to other cultures and languages.
- We are collecting a dataset with other modalities (e.g., eye movement) and extracting task-agnostic features from them.

Selected References

- Kathleen C Fraser, Jed A Meltzer, and Frank Rudzicz. Linguistic features identify alzheimer’s disease in narrative speech. *Journal of Alzheimer’s Disease*, 49(2):407–422, 2016.
- Daniel Kempler. Language changes in dementia of the alzheimer type. *Dementia and communication*, pages 98–114, 1995.
- Vaden Masrani. Detecting dementia from written and spoken language. Master’s thesis, University of British Columbia, 2018.
- Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. Hierarchical attention networks for document classification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1480–1489, 2016.