Entangled Meanings: Classification and Ambiguity Resolution in Near–Term QNLP

Chi Zhang, Akriti Kumari, Damir Cavar

Indiana University at Bloomington - NLP-Lab

Problem Statement

A significant effort in Natural Language Processing (NLP) is concerned with accurately classifying text and resolving linguistic ambiguities, especially as data complexity increases [1]. Although QNLP experiments [2, 3] have been done on quantum computers, the datasets are far from realistic. We explore various combinations of word embedding, dimension reduction, and quantum encoding algorithms on standard lambeq dataset [4] and a more realistic Amazon review dataset [5], as well as ambiguity resolution on a larger corpus (listed in the abstract), aiming to demonstrate the practical applicability of quantum computing in NLP tasks and extend the boundaries of current QNLP research.

Methodology

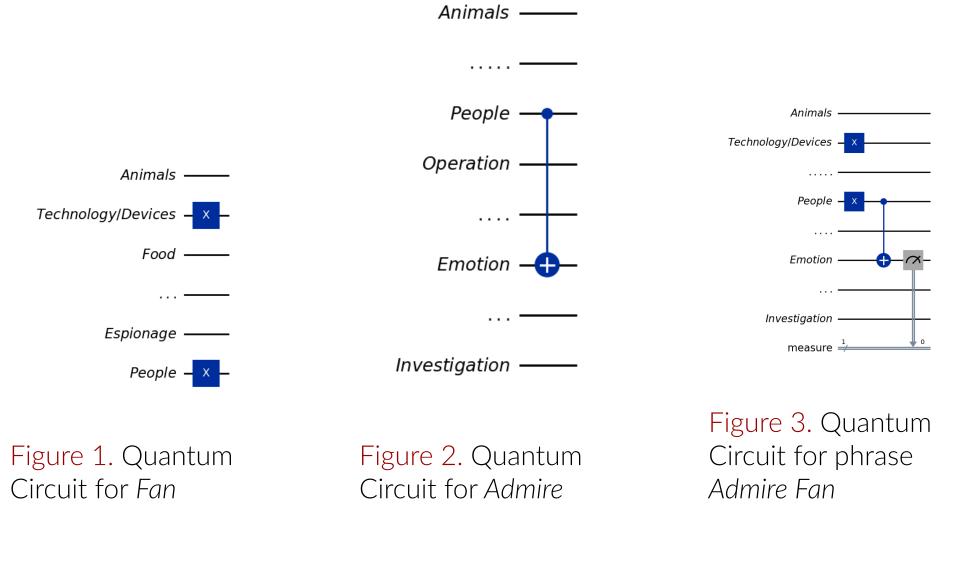
- A. Classification
 - Used lambeq and Amazon review datasets, converting texts with Word2Vec (gensim 4.1.2) [6] and spaCy [7], and applying PCA, LDA, t-SNE, from scikit-learn[8] and UMAP [9] for dimension reduction.
 Employed amplitude and divide-and-conquer encoding[10] with pennylane 0.36, training models with 15 iterations and 150 steps per iteration using a 6:2:2 train:validation:test ratio.
 Evaluated train, validation, and test accuracies for each dataset, vectorizer, dimension reduction, and quantum encoding combination to identify the most efficient configurations for limited computing resources

Contributions & Conclusion

- Classification
 - Achieved test accuracy in Table 1 on lambeq and Amazon review datasets on default.qubit in pennylane 0.36, with accurracy > 80% highlighted.
 - Achieved 100% test accuracy on the lambeq dataset using only 1 qubit with UMAP and quantum encoding, while authors in [2] used 5 qubits and in [3] used 4 qubits.
 - Test accuracy ranged from 55% to 72.5% on Amazon reviews, competitive with 57% to 62% [3] on IMDB [11], highlighting both the potential and limitations of QML.

dataset	vectorizer	reduction	quantum encoding	num_qubits	accuracy_train	accuracy_val	accuracy_test
lambeq	Word2Vec	PCA	amplitude	4	0.859	0.6154	0.7308
		PCA	dc	4	0.7821	0.8077	0.8846
		TSNE	amplitude	1	0.6282	0.6923	0.5769
		TSNE	dc	1	0.6026	0.6538	0.5385
		UMAP	amplitude	1	0.9359	0.8846	0.9615
		UMAP	dc	1	0.8205	0.9231	0.7308
		NONE	amplitude	8	0.9359	0.9615	0.9615
	spaCy	PCA	amplitude	4	0.6795	0.8462	0.6154
		PCA	dc	4	0.6795	0.7308	0.6923
		TSNE	amplitude	1	0.5897	0.6538	0.6923
		TSNE	dc	1	0.6538	0.6923	0.6923
		UMAP	amplitude	1	1.0	1.0	1.0
		UMAP	dc	1	0.9359	1.0	0.9231
		NONE	amplitude	16	0.9615	1.0	1.0
amazon	Word2Vec	PCA	amplitude	8	0.575	0.625	0.55
		TSNE	amplitude	1	0.475	0.55	0.575
		TSNE	dc	1	0.5417	0.525	0.6
		UMAP	amplitude	1	0.475	0.6	0.575
		UMAP	dc	1	0.5083	0.6	0.725
	spaCy	PCA	amplitude	8	0.5417	0.65	0.6
		TSNE	dc	1	0.475	0.575	0.55
		UMAP	amplitude	1	0.6167	0.625	0.625
		UMAP	dc	1	0.5833	0.75	0.625
		NONE	amplitude	16	0.6167	0.7	0.575

- B. Ambiguity Resolution
 - Represented language ambiguity by modeling nouns as 16-dimensional vectors and transitive verbs as matrices, inspired by early disambiguation models [3] classifying nouns into 16 categories
 - We then convert these vectors and matrices into quantum circuits by applying X and CNOT gates. For example, the quantum circuit for the noun "Fan," "Admire" and phrase "Admire Fan" is shown in Figures 1, 2, and 3, respectively.

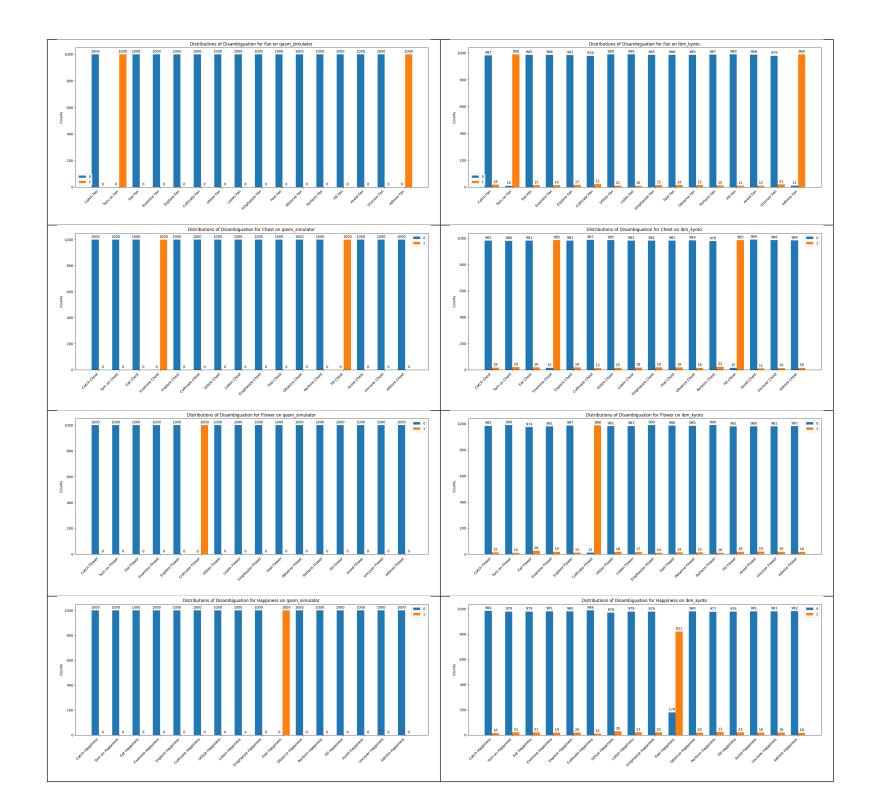


References

[1] D. Peral-García, J. Cruz-Benito, and F. J. García-Peñalvo, "Comparing Natural Language Processing and Quantum Natural Processing approaches in text classification tasks," *Expert Systems with Applications*, vol. 254, p. 124427, Nov. 2024.

Table 1. Classification results

- Ambiguity Resolution
 - Tested **16 ambiguous nouns, 34 unambiguous nouns, and 16 transitive verbs**, a much larger corpus than in [3].
 - Randomly selected 2 ambiguous and 2 unambiguous nouns for testing on ibm_kyoto and qasm_simulator.
 - Achieved 100% accuracy on qasm_ simulator and 82.1% to 98.9% on ibm_kyoto for ambiguity resolution tasks.



- [2] R. Lorenz, A. Pearson, K. Meichanetzidis, D. Kartsaklis, and B. Coecke, "QNLP in Practice: Running Compositional Models of Meaning on a Quantum Computer," *Journal of Artificial Intelligence Research*, vol. 76, pp. 1305–1342, Apr. 2023.
- [3] D. Widdows, A. Alexander, D. Zhu, C. Zimmerman, and A. Majumder, "Near-Term Advances in Quantum Natural Language Processing," *Annals of Mathematics and Artificial Intelligence*, Apr. 2024.
- [4] D. Kartsaklis, I. Fan, R. Yeung, A. Pearson, R. Lorenz, A. Toumi, G. de Felice, K. Meichanetzidis,
 S. Clark, and B. Coecke, "Lambeq: An Efficient High-Level Python Library for Quantum NLP," Oct.
 2021.
- [5] D. Kotzias, "Sentiment Labelled Sentences," 2015.
- [6] R. Rehurek and P. Sojka, "Gensim–python framework for vector space modelling," *NLP Centre*, *Faculty of Informatics, Masaryk University, Brno, Czech Republic,* vol. 3, no. 2, 2011.
- [7] M. Honnibal, I. Montani, S. Van Landeghem, and A. Boyd, "spaCy: Industrial-strength Natural Language Processing in Python," 2020.
- [8] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [9] L. McInnes, J. Healy, and J. Melville, "UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction," Sep. 2020.
- [10] I. F. Araujo, D. K. Park, F. Petruccione, and A. J. Da Silva, "A divide-and-conquer algorithm for quantum state preparation," *Scientific Reports*, vol. 11, no. 1, p. 6329, Mar. 2021.
- [11] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts, "Learning Word Vectors for Sentiment Analysis," in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, D. Lin, Y. Matsumoto, and R. Mihalcea, Eds. Portland, Oregon, USA: Association for Computational Linguistics, Jun. 2011, pp. 142–150.

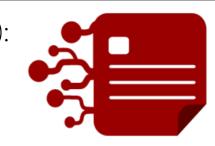
Table 2. Results for Ambiguity Resolution on Fan, Chest, Flower and Happiness

Data Availability

All code and data discussed in this work are available in the GitHub repository (https://github.com/chizhang24/entangled-meanings). The models used are all freely available online.

Natural Language Processing Lab

The NLP-Lab (https://nlp-lab.org/quantumnlp/):



https://nlp-lab.org/quantumnlp/

IEEE Quantum Week 2024

◙₩⊙

dcavar@iu.edu