

## Introduction

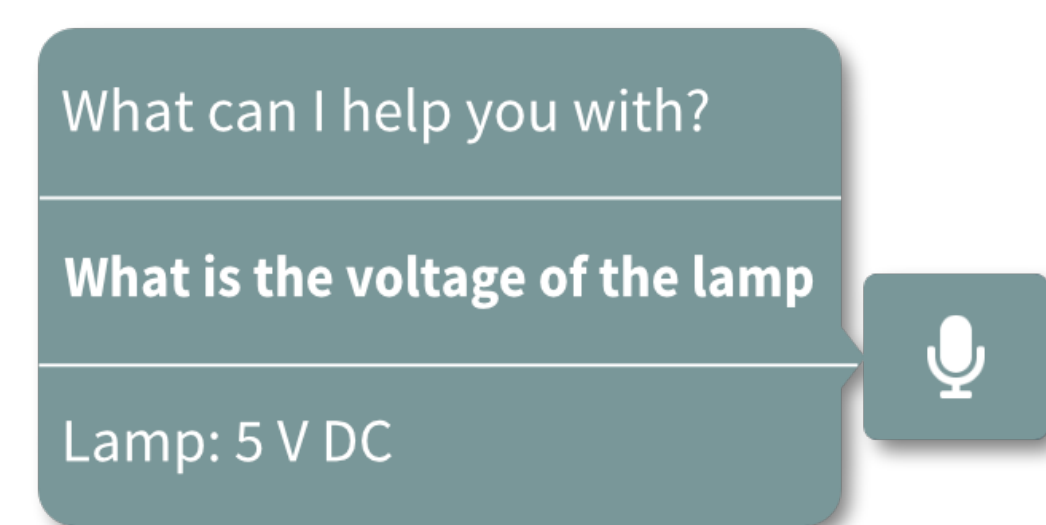
## Setting: Repair and Maintenance of Complex Machinery

- Predominantly manual tasks demanding two-handed interaction
- **Problem:** Looking up information in technical documentation interrupts task
- **Solution:** Hands-free interaction with voice assistant

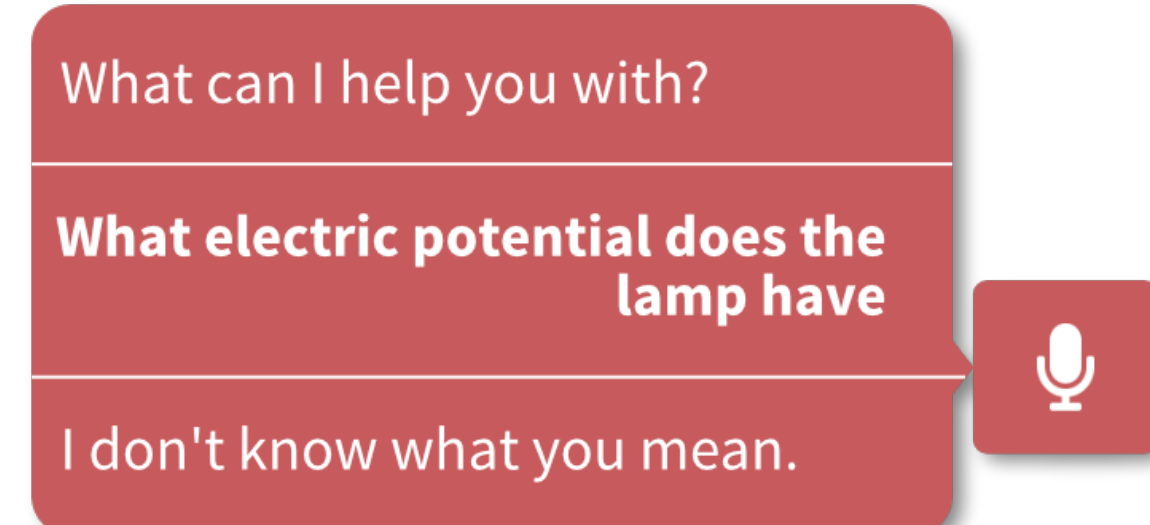


## But: Problems with Current Voice Assistants

- Require rigid input phrase structures
- User has to learn how to paraphrase requests
- **Result:** Non-natural interaction, suboptimal usability



KNOWN REQUEST PATTERN



UNKNOWN REQUEST PATTERN

## Objectives

1. **Enhance robustness** of voice assistants in the domain of Technical Service with respect to **varying phrasing**
2. **Integrate** findings into an **existing information system**
3. Develop mechanism to **adapt to user feedback**

## Language Representation Models

**Idea:** Utilize state-of-the-art language representation models

- Map words/sentences onto multi-dimensional vectors
- Vectors encode syntactic and semantic relations

## Word Vector Models

Generate vectors for each individual word

- Word2Vec [1]
- GloVe [2]
- FastText [3]

## Contextualized Vector Models

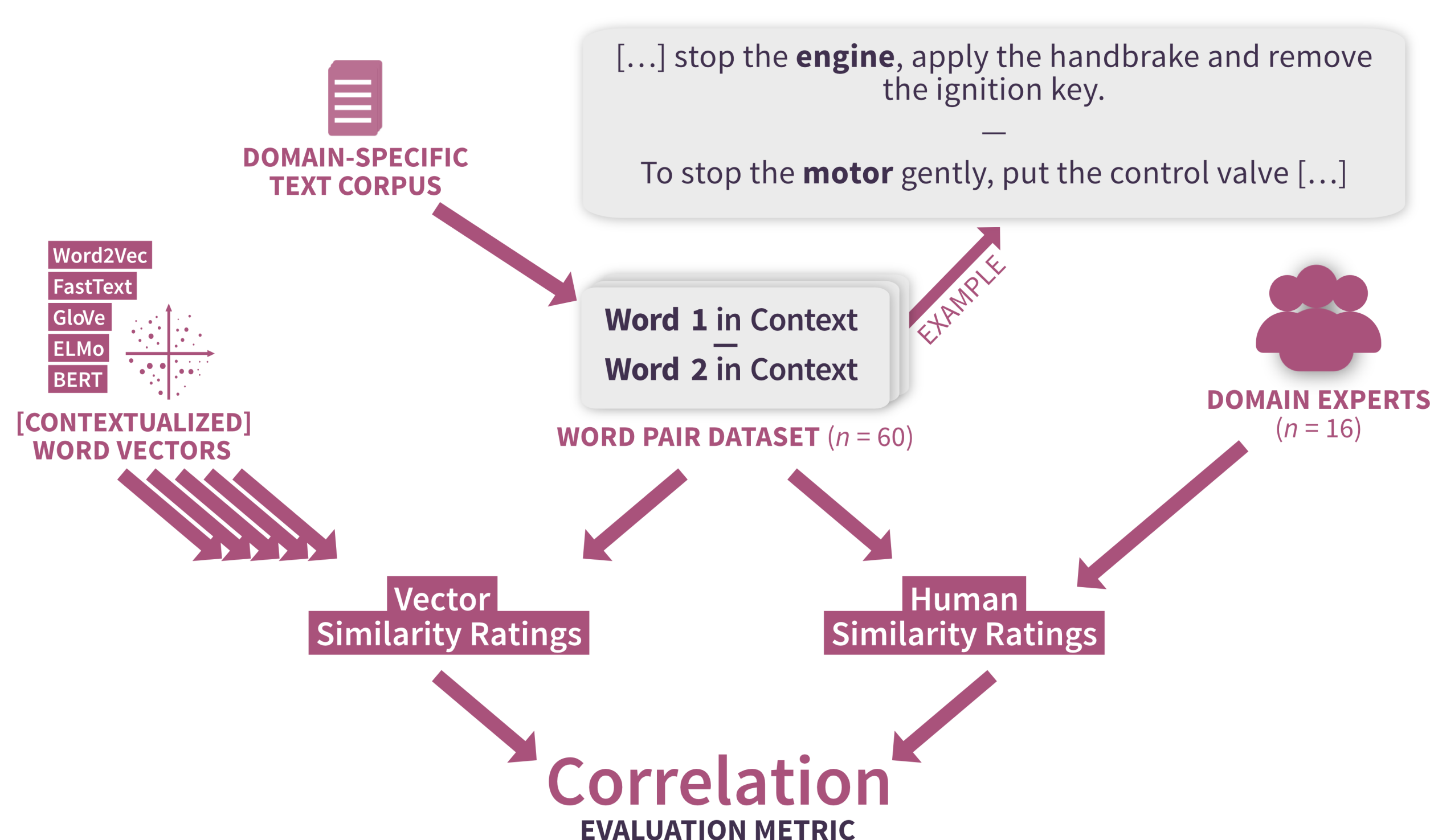
Take word context into consideration

- ELMo [4]
- BERT [5]

**Approach:** Evaluate pre-trained, self-trained and transfer-learned model instances

## Methods: Intrinsic Evaluation

**Question:** How well do vectors capture semantic similarity?



## Methods: Extrinsic Evaluation

**Question:** How well do vectors perform in a downstream task?

## Task 1 – Multiclass Classification

Classify a natural language request to one out of four categories.

## Task 2 – Binary Classification

Classify, if two natural language requests are semantically equal.

## Example

Request	Category (Task 1)	Equal (Task 2)
What is the resistance of x?	Electric Resistance	Yes
What is the ohmage value of x?	Electric Resistance	
What is the pressure at x?	Pressure	No
Which voltage should I measure at x?	Electric Potential	

## Results

## Intrinsic Evaluation

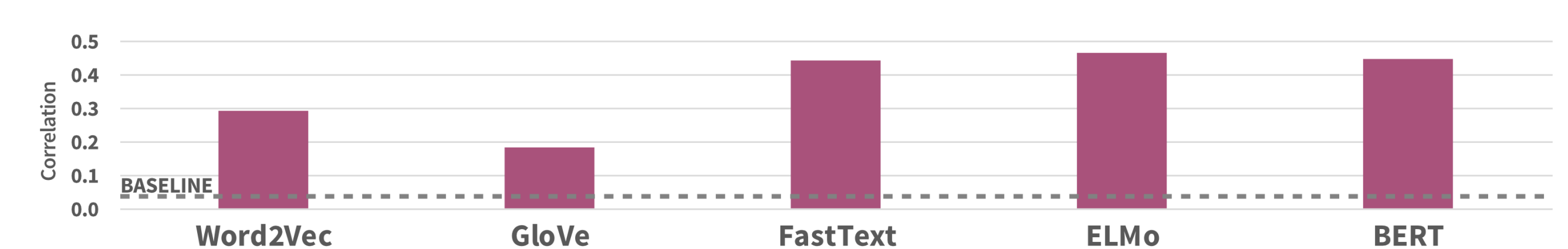


Figure 1: Spearman correlations between expert annotated ratings and the best performing instance of each model.

## Extrinsic Evaluation

	Baseline	Word2Vec	GloVe	FastText	ELMo	BERT
<b>Task 1</b>	0.8001	0.8878	0.8624	<b>0.9465</b>	0.9058	0.4907
<b>Task 2</b>	0.7936	0.9737	0.9886	0.9898	<b>0.9909</b>	0.8033

Table 1: F1 scores of best performing instance of each model.

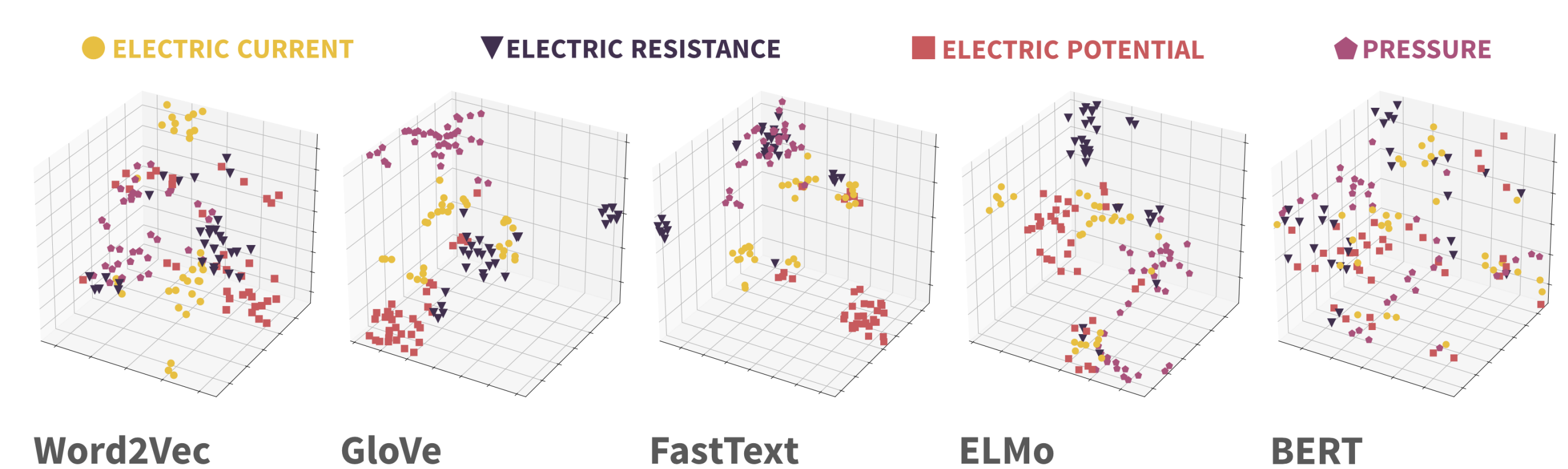


Figure 2: 3D t-SNE projections of natural language request vectors.

## Implementation

- Prototypically integrated well-performing models into information system *Service Mate*
- Asking user if a given answer was adequate enables system to learn and adapt dynamically

## References

- [1] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.
- [2] Jeffrey Pennington, Richard Socher, and Christopher Manning. Glove: Global vectors for word representation. *In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543, 2014.
- [3] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146, 2017.
- [4] Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. *In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 2227–2237, 2018.
- [5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.