Automatically responding to customers

February 13, 2019

Table of Contents

1 Introduction

2 Preliminaries

3 Benchmarking

4 Improving accuracy

5 Conclusions

Contents

1 Introduction
- Research question 1
- Research question 2

2 Preliminaries

3 Benchmarking

4 Improving accuracy

5 Conclusions

Scope

Company goal was to automatically respond to customers using a few dozen pages of text.

Updated scope: Natural language understanding (NLU)

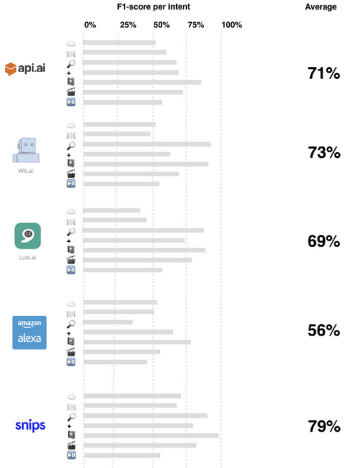
- Responding in real-time
- Few training examples

Existing NLU benchmarks

- Braun et al. [1]
- Snips [3] (next slide)
- Burtsev et al. [2]
- Botfuel [5]

Snips named-entity recognition (NER)

Their results



Question and goal

- Can an open-source NLU benchmarking tool be created?
- Develop such a tool

Question and goal

- Can the accuracy for NLU be increased?
- Improve the accuracy

Contents

1 Introduction

2 Preliminaries
- Natural language processing
- Deep learning

3 Benchmarking

4 Improving accuracy

5 Conclusions

Description of NLP field

For text or speech:

- Extract meaningful information
- Generate it

Some well-known NLP tasks

- Machine translation
- Speech recognition

Some well-known NLP tasks

- Machine translation
- Speech recognition
- Named-entity recognition

What is [London's](location) weather [tomorrow](date)?

Some well-known NLP tasks

- Machine translation
- Speech recognition
- Named-entity recognition
- Intent classification

What is [London's](location) weather [tomorrow](date)?

GetWeather

Language models

Try to model grammar

- Rule-based
- Statistical

Language models

Try to model grammar

- Rule-based
- Statistical

Statistical applications:

Task	**Example**
Spell correction	$P(\textit{my car broke}) > P(\textit{my car boke})$
Machine translation	$P(\textit{green house}) > P(\textit{house green})$
Speech recognition	$P(\textit{the red car}) > P(\textit{she read ar})$


Not tiger does that happy look
≠
That tiger does not look happy

Count-based

$$P(\text{the car broke}) = P(\text{the}) \cdot P(\text{car} \mid \text{the}) \cdot P(\text{broke} \mid \text{the car})$$

Implementation last factor

$$P(\text{broke} \mid \text{the car}) = \textsc{count}(\text{the car}) \,/\, \textsc{count}(\text{broke})$$

Approximation

$$P(\text{broke} \mid \text{the car}) \approx P(\text{broke} \mid \text{car})$$

Count-based

$$P(\text{the car broke}) = P(\text{the}) \cdot P(\text{car} \mid \text{the}) \cdot P(\text{broke} \mid \text{the car})$$

Implementation last factor

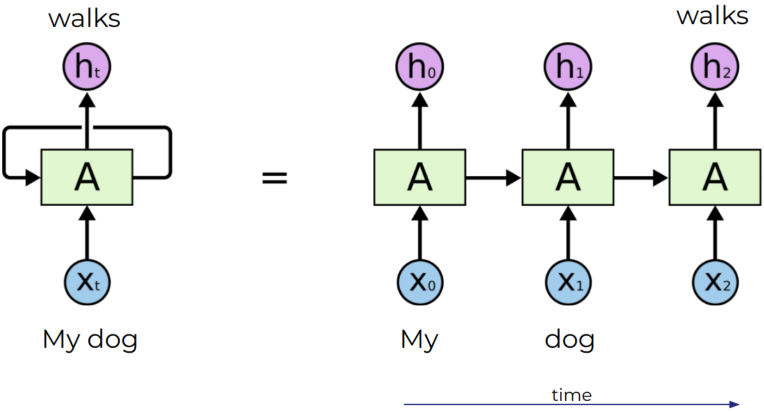
$$P(\text{broke} \mid \text{the car}) = \textsc{count}(\text{the car}) \;/\; \textsc{count}(\text{broke})$$

Approximation

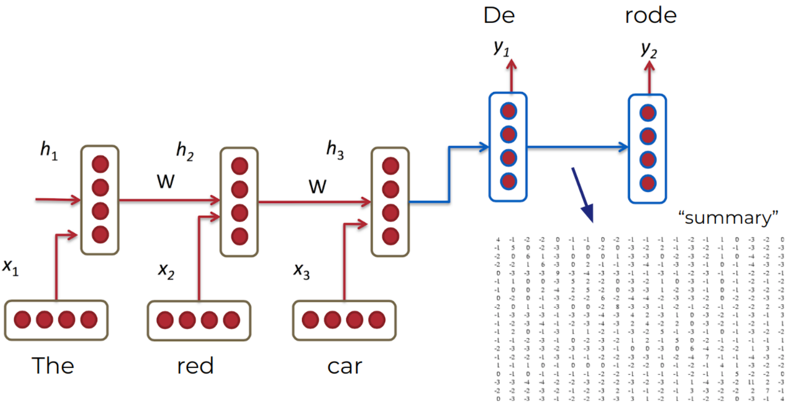
$$P(\text{broke} \mid \text{the car}) \approx P(\text{broke} \mid \text{car})$$

Insufficient history; not mobile-friendly

Recurrent neural networks



Translating



Insufficient history

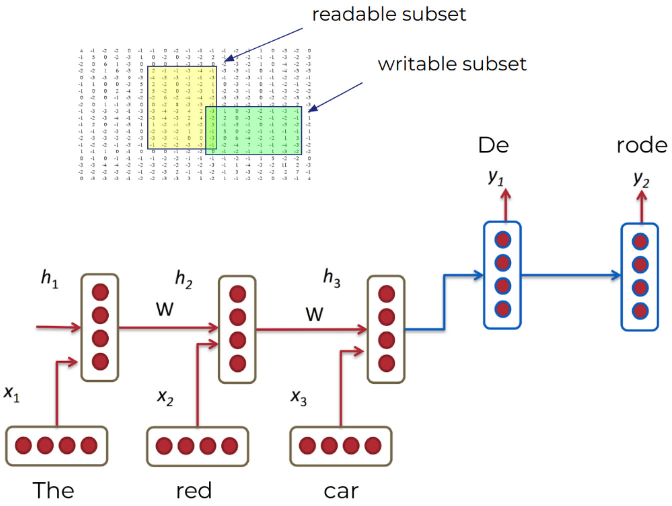
Norwegian frigate sinking has far-reaching implications.

Het zinken van het Noorse fregat heeft verstrekkende gevolgen.

Gated recurrent neural networks

- Gated recurrent unit (GRU)
- Long short-term memory (LSTM)

Gates intuition



Contents

1 Introduction

2 Preliminaries

3 Benchmarking
- Datasets
- Systems
- Tool and results

4 Improving accuracy

5 Conclusions

Overview

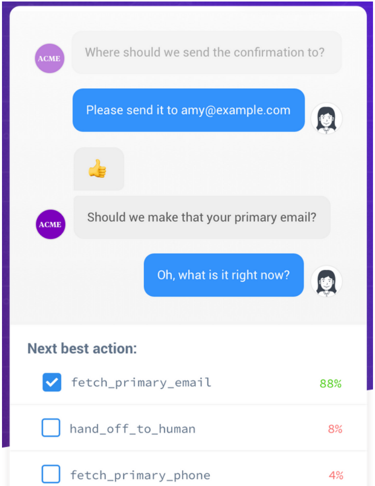
Dataset	Train	Test	Intents	Entities
WebApplications	30	54	7	1
AskUbuntu	53	109	4	3
Chatbot	100	106	2	5
Snips2017	2100	700	7	unknown

Example sentences

- WebApplications
  How can I delete my [Hunch](WebService) account?
  DeleteAccount
- Chatbot
  when is the [next](criterion) [train](vehicle) in [muncher freiheit](StationStart)?
  DepartureTime
- Snips2017
  i want to listen to [Say it Again](track) by [Blackstratblues](artist)
  PlayMusic

Rasa

- open-source
- free
- local instance

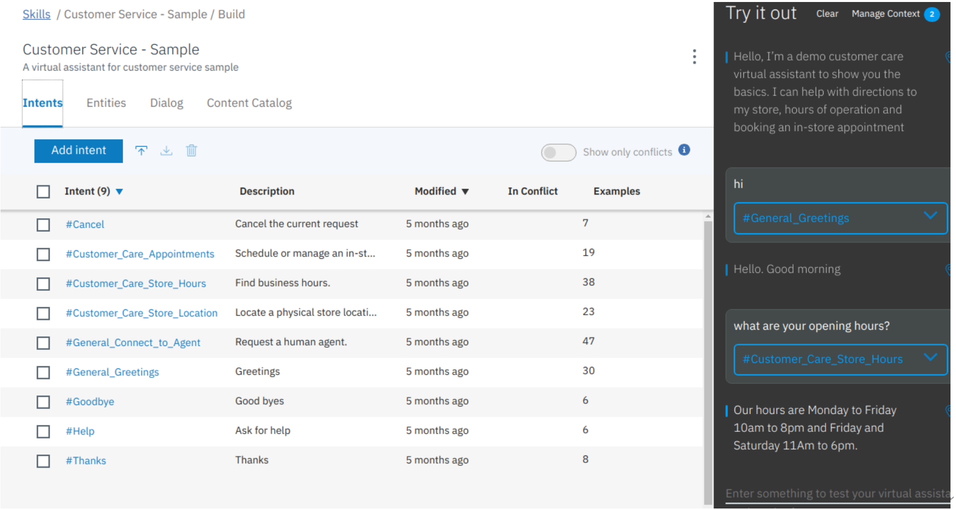


Automatically responding to customers

Rasa training data format

```
## intent:check_balance
- what is my balance <!-- no entity -->
- how much do I have on my [savings](source_account) <!-- entity "source_accour
- how much do I have on my [savings account](source_account:savings) <!-- synor
- Could I pay in [yen](currency)?  <!-- entity matched by lookup table -->

## intent:greet
- hey
- hello

## synonym:savings   <!-- synonyms, method 2 -->
- pink pig

## regex:zipcode
- [0-9]{5}

## lookup:currencies   <!-- lookup table list -->
- Yen
- USD
- Euro
```

IBM Watson Conversation



Automatically responding to customers

Tool: BENCH

- Python
- Docker containers
- API calls
- Not object-oriented[1]

[1] Steven Lott, Functional Python Programming

Results

System	Source	Ask-Ubuntu	Chatbot	Web-Apps
Rasa:0.5-mitie	Braun et al.	0.862	0.981	0.746
Microsoft LUIS	Braun et al.	0.899	0.981	0.814
Watson	Braun et al.	0.917	0.972	0.831
Rasa:0.13.7-mitie	BENCH	0.881		0.763
Rasa:0.13.8-spacy	BENCH	0.853	0.981	0.627
Watson	BENCH	0.881	0.934	0.831
Dialogflow	BENCH	0.879	0.986	0.830

Contents

1 Introduction

2 Preliminaries

3 Benchmarking

4 Improving accuracy
- BERT
- Training
- Joint training
- Results

5 Conclusions

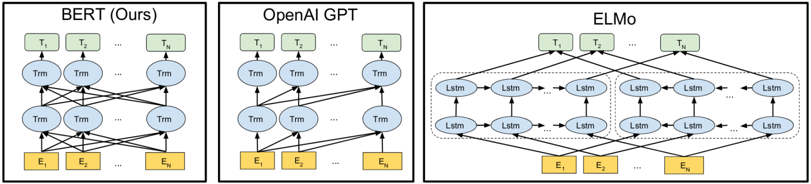
Overview

- December 2018
- SOTA 11 tasks

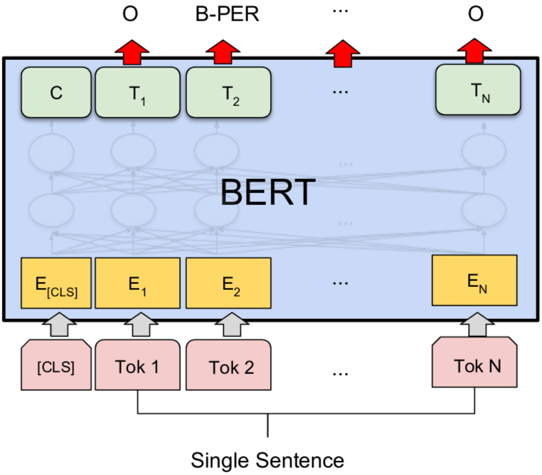
- Transformer (less sequential and $\mathcal{O}(1)$ history)
- Pre-training
- Deep bidirectionality (next slide)

Deep bidirectionality

the	...	*on*	*the*	*hill*
T_1	T_2	T_4	T_5	T_6

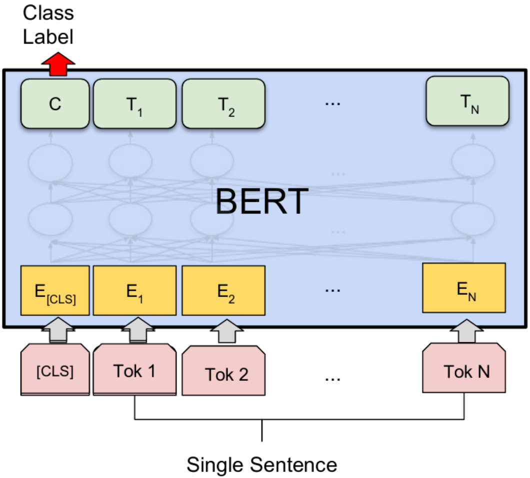


Sequential labelling



- NER SOTA

Single sentence classification



- Training time: Many hours on CPU
- Occasional near zero accuracy

Intuition for intent classification

GetWeather:

Will it rain in London tomorrow?
What is the today's temperature in Madrid?

Will it rain in <location> <date>?
What is the <date> temperature in <location>?

F_1 scores

Dataset	Steps	Method	Intent	Entity
Web-Apps	600 (twice)	Rasa	0.67 ± 0.04	
		separate	0.72 ± 0.03	0.81 ± 0.01
Ask-Ubuntu	600 (twice)	Rasa	0.84 ± 0.00	
		separate	0.82 ± 0.05	0.81 ± 0.01
Chatbot	600 (twice)	Rasa	0.98 ± 0.00	
		separate	0.84 ± 0.21	0.76 ± 0.00
Snips-2017	6000 (twice)	Rasa	0.99 ± 0.00	
		separate	0.04 ± 0.00	0.84 ± 0.00

F_1 scores

Dataset	Steps	Method	Intent	Entity
Web-Apps		Rasa	0.67 ± 0.04	
	600 (twice)	separate	0.72 ± 0.03	0.81 ± 0.01
	600	joint	0.76 ± 0.07	0.82 ± 0.01
Ask-Ubuntu		Rasa	0.84 ± 0.00	
	600 (twice)	separate	0.82 ± 0.05	0.81 ± 0.01
	600	joint	0.87 ± 0.01	0.83 ± 0.00
Chatbot		Rasa	0.98 ± 0.00	
	600 (twice)	separate	0.84 ± 0.21	0.76 ± 0.00
	600	joint	0.98 ± 0.00	0.79 ± 0.00
Snips-2017		Rasa	0.99 ± 0.00	
	6000 (twice)	separate	0.04 ± 0.00	0.84 ± 0.00
	6000	joint	0.98 ± 0.02	0.86 ± 0.00

Future work

- Code validation
- Loss function
- Entities baseline comparison
- More datasets
- Evaluate newer architectures, such as evolved ('mobile-friendly') transformer [4]

Contents

1 Introduction

2 Preliminaries

3 Benchmarking

4 Improving accuracy

5 Conclusions
- Research question 1
- Research question 2

Can an open-source NLU benchmarking tool be created?

Yes. Requirements:

- Continuous maintenance
- Support vendor APIs
- More metrics
- Multiple runs
- More datasets

Can the accuracy for NLU be increased?

Yes. Each few months a new SOTA paper.

Why BERT is suspected to have improved SOTA:

- SOTA NER
- Deeply bidirectional
- More history.

Further work: Whether accuracy improvements are significant.

References I

Braun, D., Hernandez-Mendez, A., Matthes, F., & Langen, M. (2017). Evaluating natural language understanding services for conversational question answering systems. In *Proceedings of the 18th annual SIGdial meeting on discourse and dialogue* (pp. 174–185).

Burtsev, M., Seliverstov, A., Airapetyan, R., Arkhipov, M., Baymurzina, D., Bushkov, N., … others (2018). DeepPavlov: Open-source library for dialogue systems. *Proceedings of ACL 2018, System Demonstrations*, 122–127.

References II

Coucke, A. (2017). *Benchmarking natural language understanding systems: Google, Facebook, Microsoft, Amazon, and Snips.* `https://medium.com/snips-ai/2b8ddcf9fb19`. (Accessed: 2019-01-18)

So, D. R., Liang, C., & Le, Q. V. (2019). The evolved transformer. *arXiv preprint arXiv:1901.11117*.

Trong Canh, N. (2018). *Benchmarking intent classification services - June 2018.* `https://medium.com/botfuel/eb8684a1e55f`. (Accessed: 2019-01-18)