Automatically responding to customers

February 7, 2019

Table of Contents

- 1 Introduction
- 2 Preliminaries
- 3 Benchmarking
- 4 Improving accuracy
- 5 Conclusions

Contents

- Introduction
 - Research question 1
 - Research question 2
- 2 Preliminaries
- 3 Benchmarking
- 4 Improving accuracy
- 5 Conclusions



Research question 1 Research question 2

Existing benchmarks

- Braun et al. [1]
- Snips [3] (next slide)
- Burtsev et al. [2]
- Botfuel [4]

Research question 1 Research question 2

Snips entity recognition

snips	I need a table in Sacaton at a gluten free restaurant	V
api.ai	I need a table in Sacaton at a gluten free restaurant	×
Luis.ai	I need a table in Sacaton at a gluten free restaurant	×
🕮 wit.ai	I need a table in Sacaton at a gluten free restaurant	×
amazon alexa	I need a table in Sacaton at a gluten free restaurant	×

Research question 1 Research question 2

Their results



990

Research question 1 Research question 2

Question and goal

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

Research question 1 Research question 2

Improving accuracy

How hard can it be?

Research question 1 Research question 2

Question and goal

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

Natural language processing Deep learning

Contents

- 1 Introduction
- 2 Preliminaries
 - Natural language processing
 - Deep learning
- 3 Benchmarking
- 4 Improving accuracy
- 5 Conclusions



Natural language processing Deep learning

Description of NLP field

- Extract meaningful information from text or speech
- Generate text or speech

Natural language processing Deep learning

Some well-known NLP tasks

- Machine translation
- Speech recognition
- Named-entity recognition (NER)
- Intent classification

Natural language processing Deep learning

Some well-known NLP tasks

- Machine translation
- Speech recognition
- Named-entity recognition (NER)
- Intent classification

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

Some well-known NLP tasks

- Machine translation
- Speech recognition
- Named-entity recognition (NER)
- Intent classification

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

GetWeather



Natural language processing Deep learning

Language model

- Rule-based
- Statistical

Language model

- Rule-based
- Statistical

Tries to capture grammar

Task	Example
Spell correction	P(my car broke) > P(my car boke)
Machine translation	P(green house) > P(house green)
Speech recognition	P(the red car) > P(she read ar)

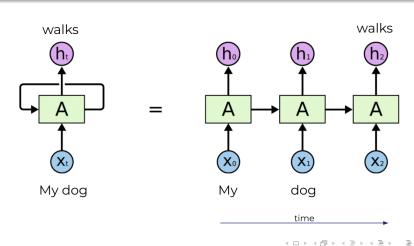


Not tiger does that happy look

That tiger does not look happy

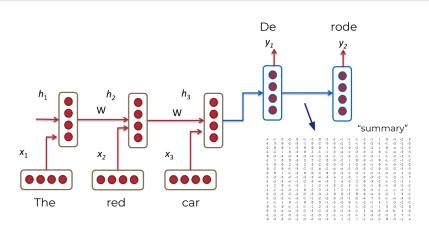
Natural language processing Deep learning

Recurrent neural networks



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Translating



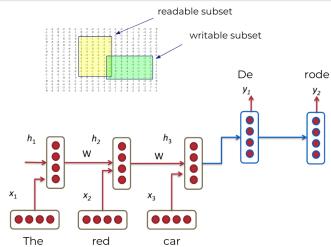
Natural language processing Deep learning

Insufficient history

Norwegian <u>frigate</u> sinking has far-reaching implications.

Het zinken van het Noorse fregat heeft verstrekkende gevolgen.

Gated recurrent neural networks



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Datasets Systems Tool and results

Contents

- 1 Introduction
- 2 Preliminaries
- 3 Benchmarking
 - Datasets
 - Systems
 - Tool and results
- 4 Improving accuracy
- 5 Conclusions



Datasets Systems Tool and results

Overview

Dataset	Train	Test	Intents	Entities
WebApplications	30	54	7	1
Chatbot	100	106	2	5
Snips2017	2100	700	7	unknown

Datasets Systems Tool and results

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

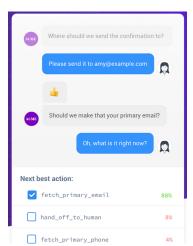
 i want to listen to [Say it Again](track) by
 [Blackstratblues](artist)

 PlayMusic

Datasets
Systems
Tool and results

Rasa

- open-source
- free
- local instance



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Datasets
Systems
Tool and results

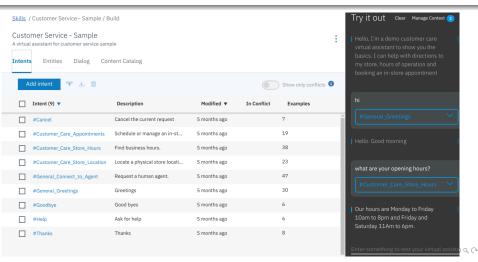
Rasa training data format

```
## intent:check balance
- what is my balance <!-- no entity -->
- how much do I have on my [savings](source_account) <!-- entity "source_account
- how much do I have on my [savings account](source_account:savings) <!-- synor</pre>
- Could I pay in [ven](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
```

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Datasets
Systems
Tool and results

IBM Watson Conversation



Datasets Systems Tool and results

Tool: BENCH

- Python
- Docker
- Not object-oriented¹

¹Steven Lott, Functional Python Programming → ← ② → ← ② → ← ② → → ② → ○ ○ ○

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

BERT Training Joint training Results

Contents

- 1 Introduction
- 2 Preliminaries
- 3 Benchmarking
- 4 Improving accuracy
 - BERT
 - Training
 - Joint training
 - Results



BERT Training Joint training Results

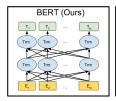
Overview

- December 2018
- SOTA 11 tasks
- Transformer (less sequential and $\mathcal{O}(1)$ history)
- Pre-training
- Deep bidirectionality

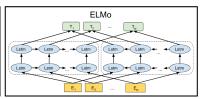
BERT Training Joint training Results

Deep bidirectionality

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

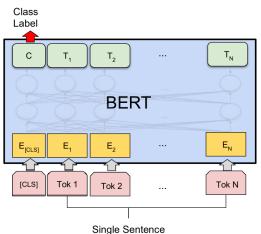






BERT Training Joint training Results

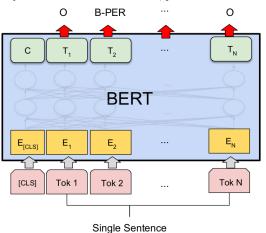
Single sentence classification



- Training time: 1.5 days
- Occasional near zero accuracy

BERT
Training
Joint training
Results

Sequential labelling



NER SOTA

BERT Training Joint training Results

Intuition

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>?

BERT Training Joint training Results

Intent

Entity

F₁ scores

Dataset Steps

	Ctcps			
Web-		Rasa	$\textbf{0.67} \pm \textbf{0.04}$	
Apps	600 (twice)	separate	$\textbf{0.72} \pm \textbf{0.03}$	$\textbf{0.81} \pm \textbf{0.01}$
		-		
Ask-		Rasa	$\textbf{0.84} \pm \textbf{0.00}$	
Ubuntu	600 (twice)	separate	$\textbf{0.82} \pm \textbf{0.05}$	$\textbf{0.81} \pm \textbf{0.01}$
Chatbot		Rasa	$\textbf{0.98} \pm \textbf{0.00}$	
	600 (twice)	separate	$\textbf{0.84} \pm \textbf{0.21}$	$\textbf{0.76} \pm \textbf{0.00}$
		·		
Snips-		Rasa	$\textbf{0.99} \pm \textbf{0.00}$	
2017	6000 (twice)	separate	$\textbf{0.04} \pm \textbf{0.00}$	$\textbf{0.84} \pm \textbf{0.00}$

Method

Introduction

BERT Training Joint training Results

Intent

 0.67 ± 0.04

F₁ scores

DatasetWeb-

2017

Steps

6000 (twice)

6000

Apps	600 (twice)	separate	$\boldsymbol{0.72 \pm 0.03}$	$\textbf{0.81} \pm \textbf{0.01}$
	600	joint	$\boldsymbol{0.76 \pm 0.07}$	$\textbf{0.82} \pm \textbf{0.01}$
Ask-		Rasa	$\textbf{0.84} \pm \textbf{0.00}$	
Ubuntu	600 (twice)	separate	$\textbf{0.82} \pm \textbf{0.05}$	$\textbf{0.81} \pm \textbf{0.01}$
	600	joint	$\textbf{0.87} \pm \textbf{0.01}$	$\textbf{0.83} \pm \textbf{0.00}$
Chatbot		Rasa	$\textbf{0.98} \pm \textbf{0.00}$	
	600 (twice)	separate	$\textbf{0.84} \pm \textbf{0.21}$	$\boldsymbol{0.76 \pm 0.00}$
	600	joint	$\textbf{0.98} \pm \textbf{0.00}$	$\boldsymbol{0.79 \pm 0.00}$
Snips-		Rasa	0.99 ± 0.00	

separate

joint

Method

Rasa

 0.04 ± 0.00

Entity

 0.84 ± 0.00

 0.86 ± 0.00

References

BERT Training Joint training Results

Future work

- Code validation
- Loss function
- Entities baseline comparison
- Datasets
- 'Mobile friendly' transformer²

²So et al., The Evolved Transformer (30 jan 2019) → ⟨₹⟩ ⟨₹⟩ ⟨₹⟩ ⟨₹⟩ ⟨₹⟩

Research question 1 Research question 2

Contents

- 1 Introduction
- 2 Preliminaries
- 3 Benchmarking
- 4 Improving accuracy
- 5 Conclusions
 - Research question 1
 - Research question 2



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.



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