## Neural Models of Response Selection for Bootstrapping Dialogue Systems

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## Creating Task-based Dialogue Systems

Convincing Application

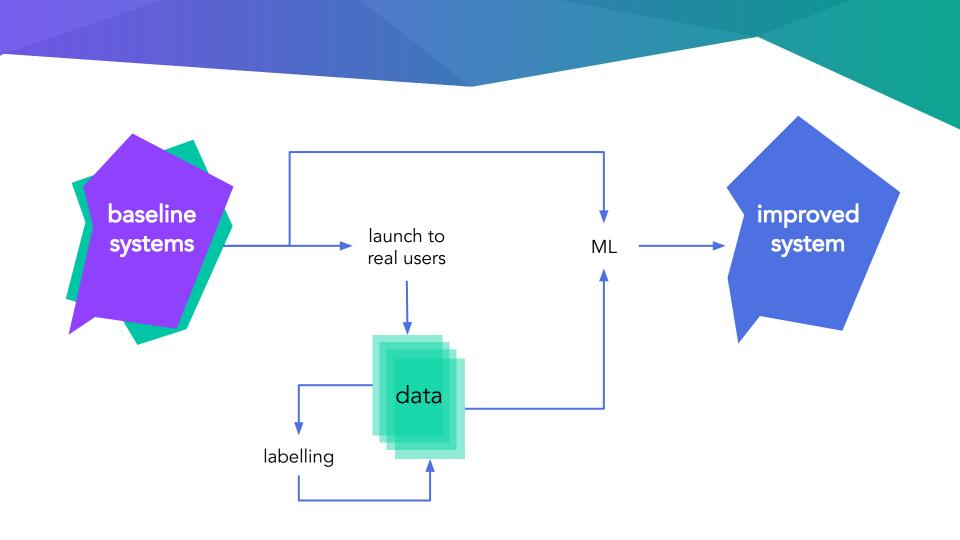
solves a real problem

Meaningful Evaluation

can measure progress

Annotaated Data

is machinelearnable

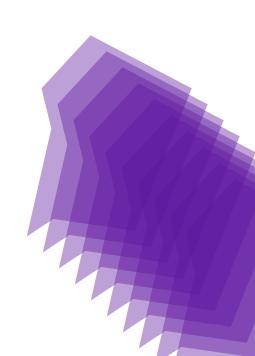


how do we get a

baseline system?

intent classifiers slot-value recognisers response selection/generation

xskills xdomains xlanguages



# reliance on annotated data?

how can we minimise

how can we scale better?

(skills, domains, languages...)

# conversational response

by using large pre-trained

models that encapsulate

knowledge of

### Pre-training in NLP

- recent trend to pre-train large models of language, then fine-tune BERT, ELMo, GPT etc.
- uses unlabelled text + unsupervised objective same idea as cbow, skip gram, skip thought etc.
- learns general representations of text, useful for downstream tasks

### PolyAl Conversational Datasets

### Reddit



3.7 billion comments from online discussions on many topics



727 million examples

### **OpenSubtitles**



over 400 million lines of subtitles from movies and TV



316 million examples

### AmazonQA



over 3.6 million product question-answer pairs



3.6 million examples

github.com/PolyAI-LDN/conversational-datasets

### Public Conversational Datasets

	~ Turns	Annotations	
DSTC 2&3	10 <sup>4</sup>	response, ASR, SLU	
MultiWoz	10 <sup>5</sup>	response, NLU	
DSTC7 Reddit	10 <sup>6</sup>	response, entities	
DSTC7 Ubuntu	10 <sup>6</sup>	response	
PolyAl AmazonQA	10 <sup>6</sup>	product, response	
PolyAl OpenSubtitles	10 <sup>8</sup>	'response'	
PolyAl Reddit	10 <sup>9</sup>	response	

### Next word prediction

### Masked word prediction

The launch of ■ 's second lunar mission has been ??? less than an hour before the scheduled blast- ■ , due to a ■ problem.

apple called halted celebrate passport

### Response Selection

Any recommendations for short trips from Singapore?

It doesn't feel like July.
That type of music isn't really my cup of tea.

→ Bintan is just a quick ferry trip away.

You have to try the vegetarian Haggis!
I'd do a short trip to Paris.

. . .

### Response Selection

- large conversational datasets
- representations encode conversational cues
- encodes full sentences
- directly applicable to retrieval-based dialogue

### Language Modelling

- large text datasets
- representations encode word/phrase/sentence cues
- encodes words contextually
- maybe applicable to generation/scoring

a lot of the power of neural techniques is finding good embeddings / encodings

- so learn encoder model on large conversational data
- then use various tricks and small models on the learned vector space for domain specific tasks

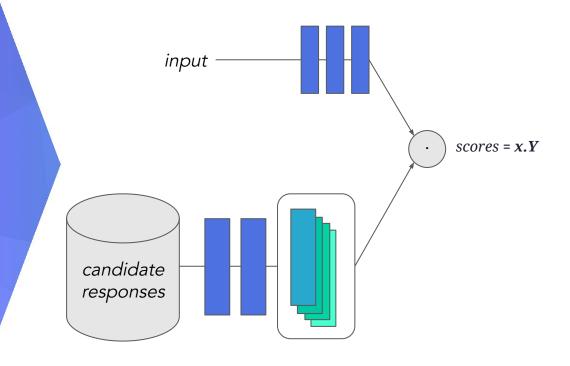
## Dual Encoders for Response Selection

dual encoder dot product model

- gmail smart reply
- universal sentence encoder

trained to give a high score for the response found in the data, low score for random responses

final score of an input and response is a dot-product of two vectors



network encodes a batch of inputs to vectors:

 $\boldsymbol{X}_1 \quad \boldsymbol{X}_2 \quad \dots \quad \boldsymbol{X}_N$ 

and responses to vectors:

 $y_1$   $y_2$  ...  $y_N$ 

$x_1, y_1$	$\boldsymbol{x}_1.\boldsymbol{y}_2$	$\boldsymbol{x}_1,\boldsymbol{y}_3$	$\boldsymbol{x}_1,\boldsymbol{y}_4$	$\boldsymbol{x}_1.\boldsymbol{y}_5$
$\boldsymbol{x}_2.\boldsymbol{y}_1$	$\boldsymbol{x}_2.\boldsymbol{y}_2$	$\boldsymbol{x}_2,\boldsymbol{y}_3$	$\boldsymbol{x}_2.\boldsymbol{y}_4$	$\boldsymbol{x}_2.\boldsymbol{y}_5$
$\boldsymbol{x}_3.\boldsymbol{y}_1$	$\boldsymbol{x}_3.\boldsymbol{y}_2$	$x_3,y_3$	$\boldsymbol{x}_3.\boldsymbol{y}_4$	$\boldsymbol{x}_3.\boldsymbol{y}_5$
$x_4.y_1$	$\boldsymbol{x}_4.\boldsymbol{y}_2$	$\boldsymbol{x}_4.\boldsymbol{y}_3$	$\boldsymbol{x}_4.\boldsymbol{y}_4$	$\boldsymbol{x}_4.\boldsymbol{y}_5$
$\boldsymbol{x}_{5}, \boldsymbol{y}_{1}$	$\boldsymbol{x}_{5}.\boldsymbol{y}_{2}$	$\boldsymbol{x}_{5},\boldsymbol{y}_{3}$	$\boldsymbol{x}_5.\boldsymbol{y}_4$	$\boldsymbol{x}_5.\boldsymbol{y}_5$

the N x N matrix of all scores is a fast matrix product.

large improvement in 1 of 100 ranking accuracy over binary classification.

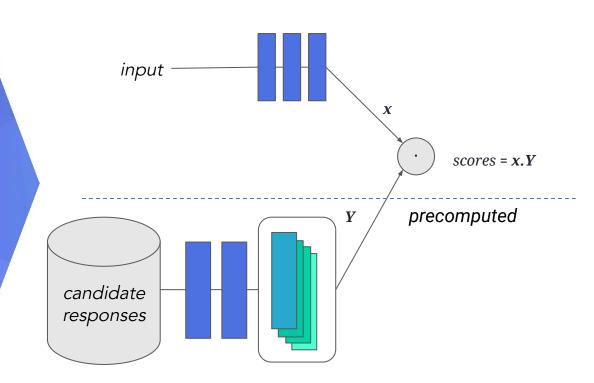
$x_1, y_1$	$\boldsymbol{x}_1.\boldsymbol{y}_2$	$\boldsymbol{x}_1, \boldsymbol{y}_3$	$\boldsymbol{x}_1.\boldsymbol{y}_4$	$\boldsymbol{x}_1.\boldsymbol{y}_5$
$\boldsymbol{x}_2, \boldsymbol{y}_1$	$\boldsymbol{x}_2.\boldsymbol{y}_2$	$\boldsymbol{x}_2.\boldsymbol{y}_3$	$\boldsymbol{x}_2.\boldsymbol{y}_4$	$\boldsymbol{x}_2.\boldsymbol{y}_5$
$\boldsymbol{x}_3.\boldsymbol{y}_1$	$\boldsymbol{x}_3.\boldsymbol{y}_2$	$x_3y_3$	$\boldsymbol{x}_3.\boldsymbol{y}_4$	$\boldsymbol{x}_3.\boldsymbol{y}_5$
$\boldsymbol{x}_{4},\boldsymbol{y}_{1}$	$\boldsymbol{x}_4.\boldsymbol{y}_2$	$\boldsymbol{x}_4.\boldsymbol{y}_3$	$\boldsymbol{x}_4.\boldsymbol{y}_4$	$\boldsymbol{x}_4.\boldsymbol{y}_5$
$\boldsymbol{x}_{5}.\boldsymbol{y}_{1}$	$\boldsymbol{x}_{5}, \boldsymbol{y}_{2}$	$\boldsymbol{x}_{5},\boldsymbol{y}_{3}$	$\boldsymbol{x}_5.\boldsymbol{y}_4$	$\boldsymbol{x}_5.\boldsymbol{y}_5$

$$m{x}_i = f( ext{input } i)$$
 $m{y}_j = g( ext{response } j)$ 
 $m{S}_{ij} = m{x}_i \cdot m{y}_j$ 
 $P( ext{response } j \mid ext{input } i) \propto e^{Sij}$ 
 $-\log P( ext{example } i) = - m{S}_{ii} + \log \Sigma_j e^{Sij}$ 
"dot product loss"

# Precomputation for dot product model

the representations of the candidates Y can be precomputed

approximate nearest neighbor search can speed up the top N search



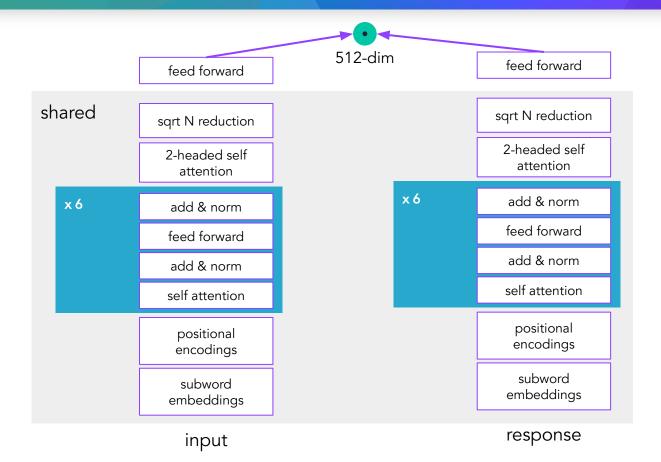
at inference, a user query has N words, there are M responses with  $N_R$  words each

- dot product model
  - O(N) to encode input to vector space
  - $O(\log M)$  to find top scoring response with approximate search
- general sequence model (e.g. BERT next sentence scoring)
  - $O(M(N + N_p))$  to score all responses
  - O(M) to find top response

## 1-of-100 accuracy

how often the correct response is ranked top vs 99 random

## PolyAl Encoder



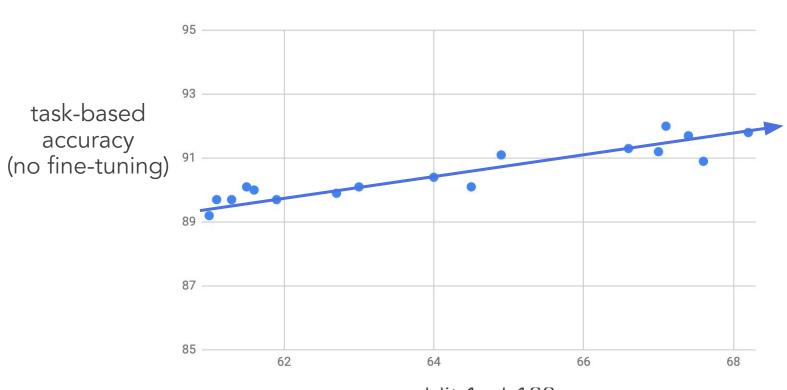
## PolyAl Encoder

	reddit 1-of-100			
		accuracy		
	TF-IDF	26.70/		
keyword-based		26.7%		
,	BM25	27.6%		
	ELMo	19.3%		
MAP dot product models	BERT	24.5%		
	USE	40.8%		
	USE_QA	46.3%		
	BERT dot-product model	55.0%		
PolyAl Encoders	n-grams	61.3%		
i olyAl Elicodeis	subwords	68.2%		

### PolyAl Encoder

resource-constrained optimization: pick the best model after training 18 hours on 12 GPUs

- fast ML engineering cycle, rapid progress
- we own the whole training pipeline
- training costs under \$100
- model runs fine on CPU
- final model is 40MB



reddit 1-ot-100 (progress over 3 weeks)

## intent classification

### Intent Classification

### initiate-booking

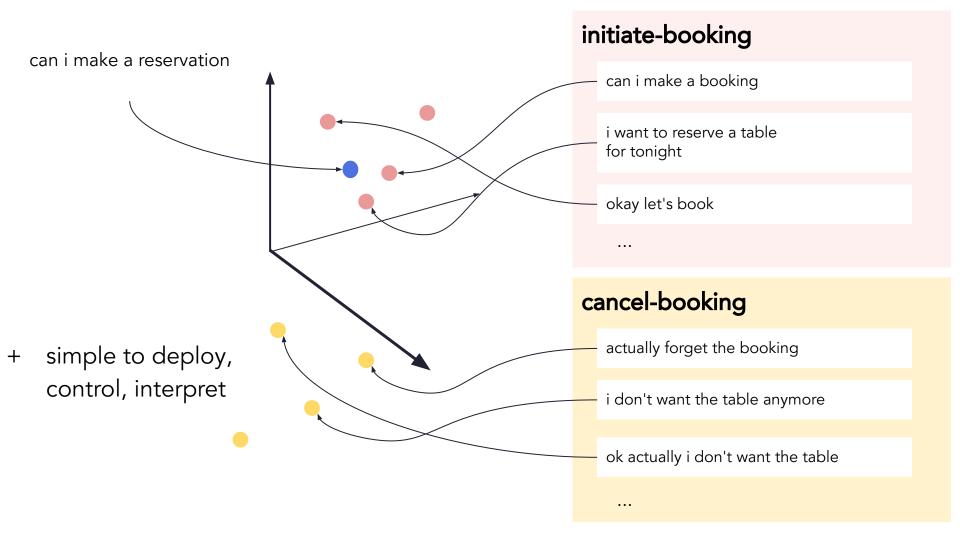
can i make a booking can i reserve a table okay i want to book a table for tonight

### cancel-booking

cancel it i don't want the table anymore

### restart

let's start over forget this



### Intent classification

- can train an MLP on top of encoding representation
- can jointly fine-tune the encoding parameters

- can treat similarity in encoding space as as a kernel
  - SVM (more interpretable, encoding-agnostic)

## Intent Evaluation

		PolyAl Encoder			
		PolyAl QQ PolyAl SVM PolyAl ML			
Banking	Banking small		83.1%	81.8%	
	medium	82.5%	91.0%	90.4%	
	large	87.7%	93.1%	92.7%	
	e-commerce		94.1%	94.5%	
company FAQ		63.8%	64.5%	64.5%	

### Intent Evaluation

	PolyAl Encoder							
		PolyAl QQ	PolyAl SVM	PolyAl MLP	USE QQ	USE FT	BERT FT	RASA FT
Banking	small	68.3%	83.1%	81.8%	67.3%	80.4%	80.4%	63.4%
	medium	82.5%	91.0%	90.4%	83.8%	89.8%	90.9%	84.0%
	large	87.7%	93.1%	92.7%	87.8%	92.2%	92.9%	89.2%
9	e-commerce	92.0%	94.1%	94.5%	90.5%	94.0%	94.4%	92.1%
cc	mpany FAQ	63.8%	64.5%	64.5%	55.8%	62.4%	65.0%	55.4%

### Intent Evaluation

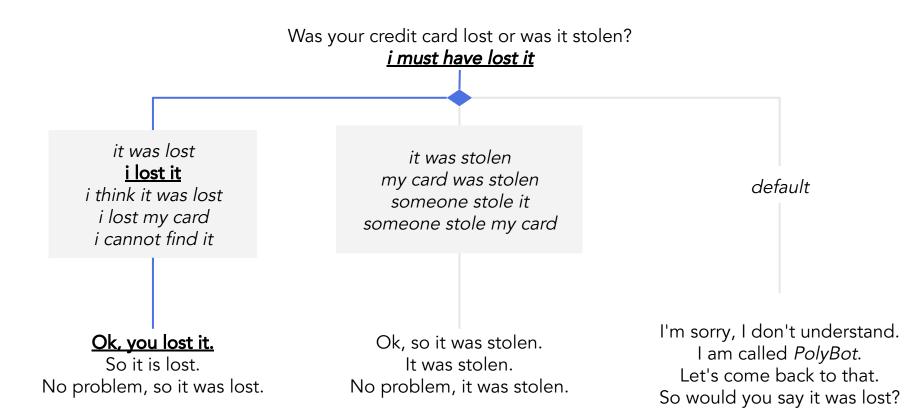
	PolyAl Encoder							
		PolyAl QQ	PolyAl SVM	PolyAl MLP	Twilio	MS Luis	IBM Watson	Dialogflow
Banking	small	68.3%	83.1%	81.8%	65.6%	69.0%	73.3%	79.6%
	medium	82.5%	91.0%	90.4%	83.7%	80.7%	87.0%	86.4%
	large	87.7%	93.1%	92.7%	89.6%	86.9%	90.6%	86.9%
	e-commerce	92.0%	94.1%	94.5%	91.3%	92.0%	92.1%	89.8%
co	ompany FAQ	63.8%	64.5%	64.5%	55.7%	55.1%	57.8%	53.2%

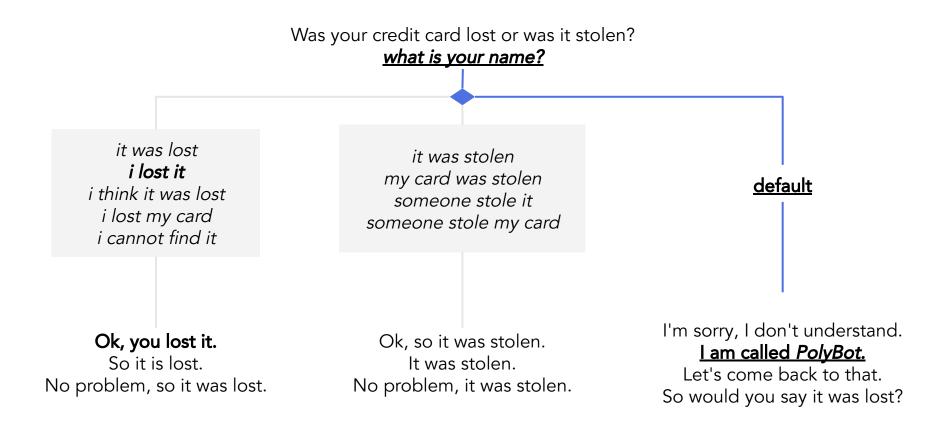
# simple bot building

# Simple bot building

quick prototyping of dialogues flows using the shared input response embedding space







# Simple bot building

- fast prototyping / proof of concept

- system design interface is entirely text no need to train additional models
- flows can be guaranteed by adding text

# restaurant search

### **DSTC 2 & 3**

#### hello I am looking for a cheap place in the east

> inform(pricerange=cheap, area=east)

sure, what type of food?

> request(food)

#### i want gastropub food

> inform(food=gastropub)

there are no cheap places serving gastropub in the east.

> inform(name=none, area=east, pricerange=cheap)

how about any pricerange? and i need to know if they have wifi.

> inform(pricerange=dontcare) request(has\_wifi)

The King's Arms is a nice place in the east of town serving gastropub food. It has wifi.

> offer(name="The King's Arms", area=east, food=gastropub, has\_wifi=true)

### **DSTC 2 & 3**

explicit semantics forces unnaturally constrained dialogues users need to know the ontology

- requires special annotated data, one specialised model per 'slot'

### **DSTC 2 & 3**

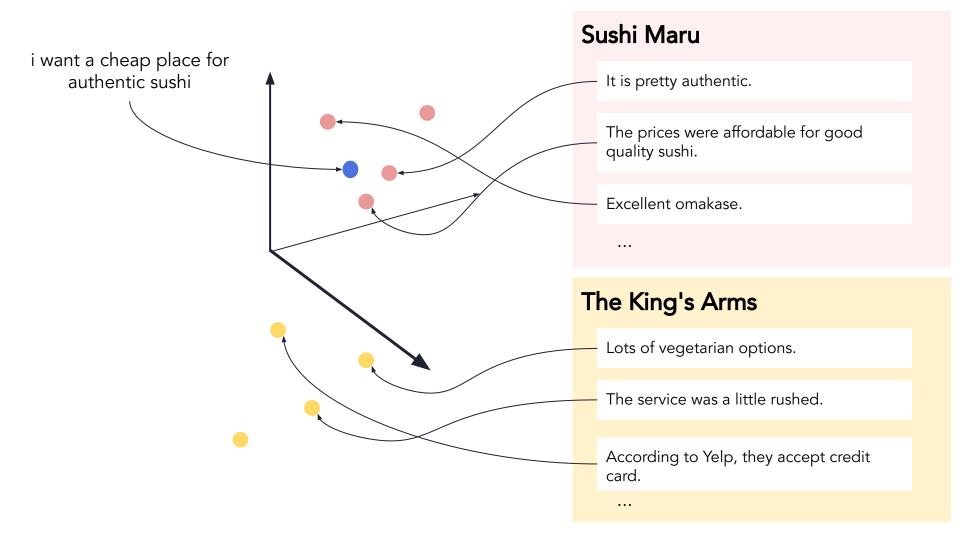
- some slots are necessary

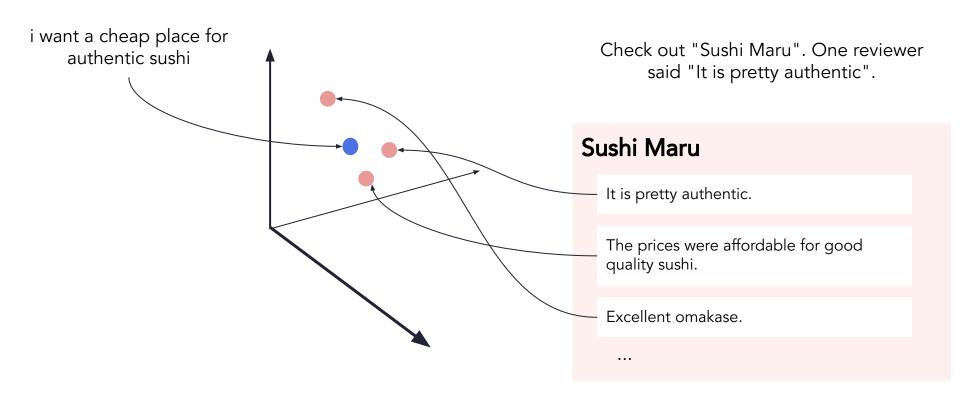
number of people, booking time, name

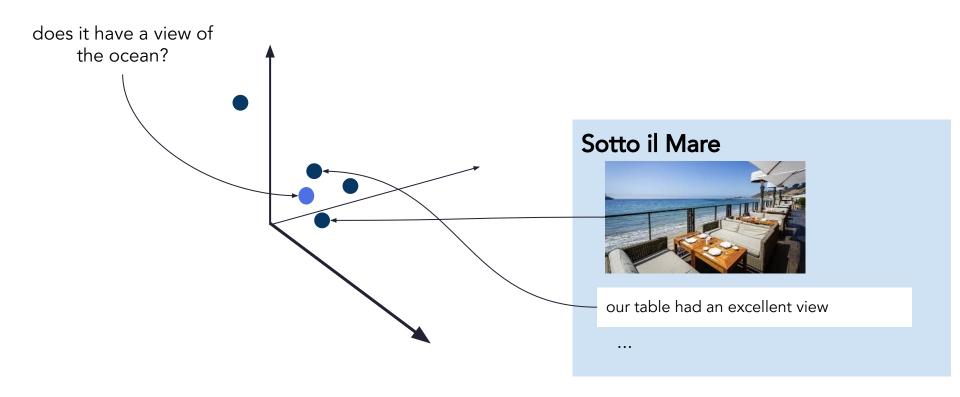
- some might not be

food, price range, has wifi, has vegetarian, has vegan, serves cocktails....

use all sentences in all reviews of all restaurants in a city
treat dialogue as an iterative search
perform search in implicit vector space learned by encoders







70 1 739

Found 2 Bars, Nightlife, Breakfast & Brunch, Seafood, Pubs... etc. places

i want a bar with good craft beer





#### BrewDog Edinburgh

Pubs, Bars, Pizza, Gastropubs, Burgers, Nightlife





#### The Beer Kitchen By Innis & Gunn

Breakfast & Brunch, Seafood, Bars, Nightlife





#### The Elephant House

Restaurant in Old Town. Brasseries, Coffee & Tea, Food, British, Sandwiches, Cafes, and Scottish

where did JK rowling write Harry Potter





• "After all, if JK Rowling was inspired maybe it can rub off?"

#### The Elephant House

Restaurant in Old Town. Brasseries, Coffee & Tea, Food, British, Sandwiches, Cafes, and Scottish

can i book a table for 2







What date and time?

## Search procedure

encode user text with input encoder

if restart intent detected, restart

2. find potential answers in restaurant texts

hundreds of thousands of texts

- 3. convert scores into probabilities
- 4. constrain the set of active restaurants to those that make up the head of the distribution

### Restaurant search

- entirely powered by a single model, trained on hundreds of millions of examples
- bootstrapped using only raw text representations- restaurants + reviews + facts
- allows more natural search, not bottlenecked by explicit semantics / ontology

### Value Extraction

limit slots to obvious values that the system needs to extract

booking time & date, your name, number of people

value extraction can benefit from pre-trained representations

- see our blog post on Neural language understanding of people's names

Hello, Thank you for contacting The Haywain, I am a digital agent, how can I help?

do you have any veggie burgers?

Yes, we have a popular Vegan Burger with BBQ Soya for £11.49, and will be happy to help with your requirements.



nice. ok can i book a table for 2

What day would you like to book for?

for tomorrow at 6 in the evening

No problem, we have a table for you for 2 people, tomorrow at 06:00PM. Shall I book that for you?

# Response Selection for Bootstrapping Dialogue

### efficient task tailored to dialogue

smaller cheaper faster models

### robust performance on downstream tasks

competitive intent classification

driven by paraphrase collection

#### powers conversational search

efficient search reduced dependency on strict ontology

