

# Conversational Al Platform for Customer Service

Nikola Mrkšić, Cofounder & CEO

### **PolyAl**

Founded in 2017



Raised \$15 million





**Published** 

100 +

Research papers, with over 4,000 citations between us

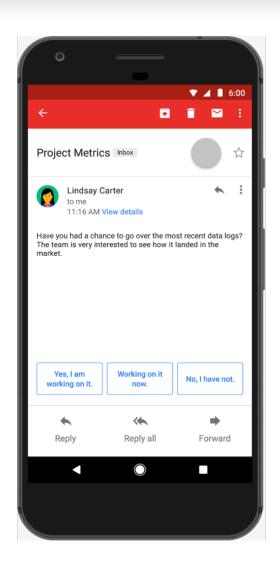


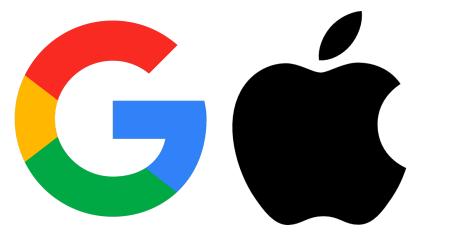




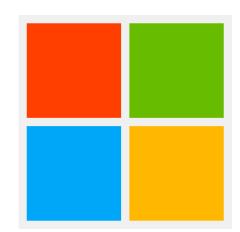


## Previously, we've worked on...









### We Work With











# **Latest Progress of Conversational Al**

# Audible now offers live customer service through Alexa devices

2 months ago Sarah Perez

Alexa devices just got a new use case: live customer service help. This morning, Amazon's e-book company Audible announced the first live customer service experience on Alexa devices, activat...



# Google's Duplex calls still frequently require human intervention

4 weeks ago Brian Heater

When Google launched Duplex with a demo at I/O last year, the audience was left wondering how much of the call was staged. The Al-based reservation booking service seemed almost too impressive to b...



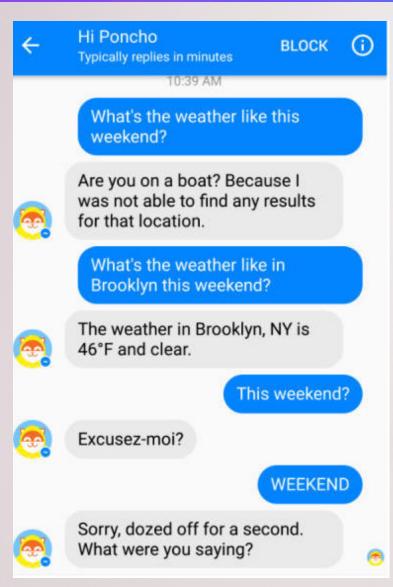
### Twilio launches Autopilot to help developers build better bots

Bots went through the hype cycle faster than a speeding roller coaster, as the promise of chatting with a computer quickly turned sour. Now, Twilio wants to take another stab at this market with th...





### **Conversational Al Today**





### Conversational AI - Where Are We?









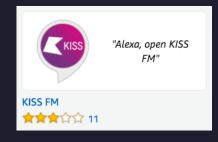




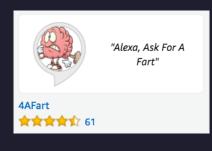


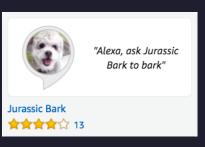


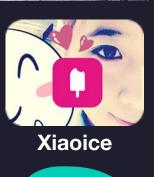


















## What Are the Challenges?

Developers have to anticipate all phrases that could be used to invoke a command

- An alarm for 8.30am.
- Set an alarm for half eight.
- Turn on my 8.30am alarm.
- Wake me up in six hours.
- Alarm at 8.30am, please.

• • •

- Extra hot.
- Very spice.
- Burning hot.
- The hottest one.
- Extra spicy please.

...

## What Are the Challenges?

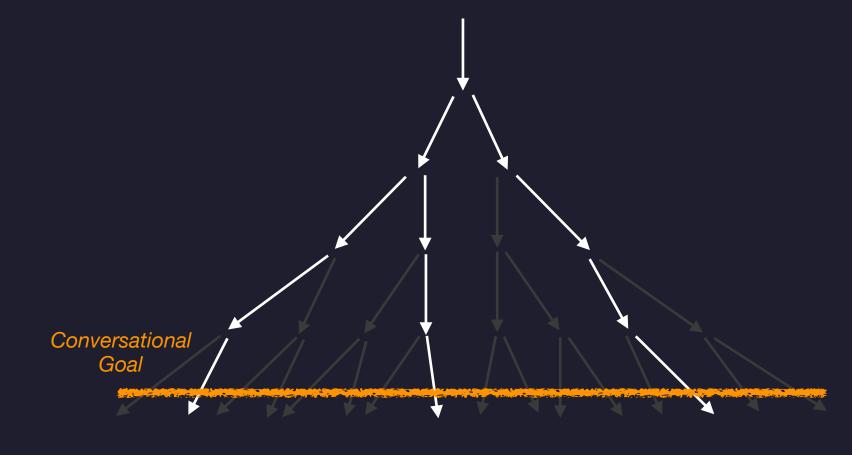
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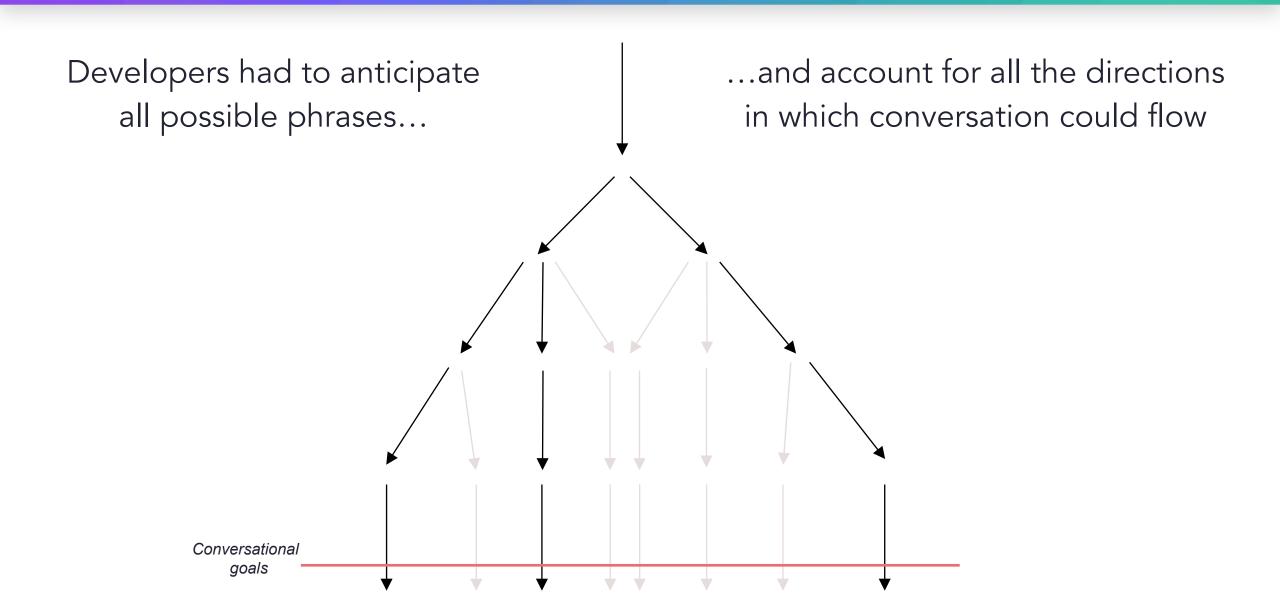
. . .

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... and they have to account for all the conversational scenarios that their users might try to follow



### Non Al Automation is Linear



### We Imagine Customer Scenarios to be Simple (Linear)

What time would you like your booking for?

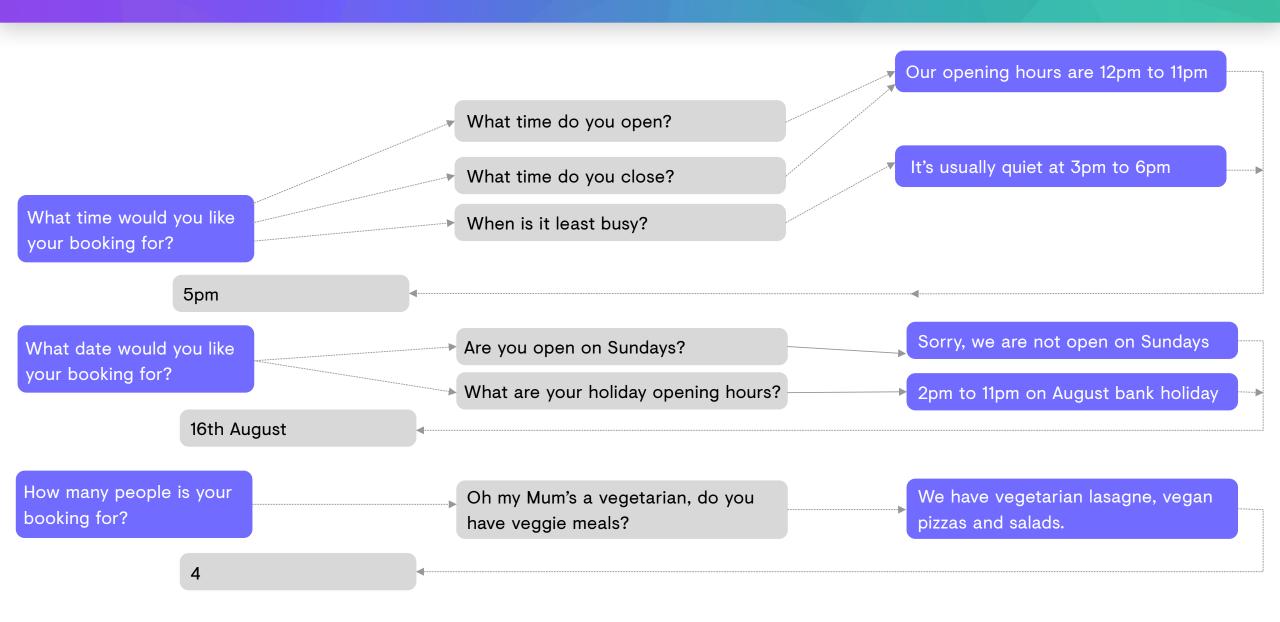
5pm

What date would you like your booking for?

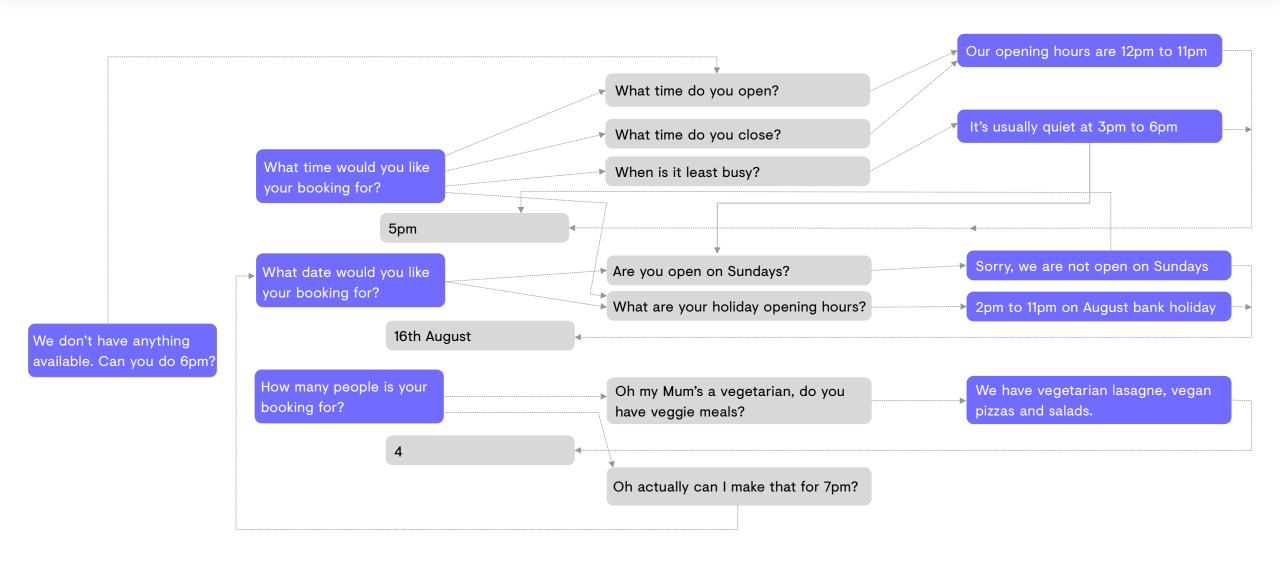
16th August

How many people is your booking for?

### **Customers Would Like to Ask Questions**

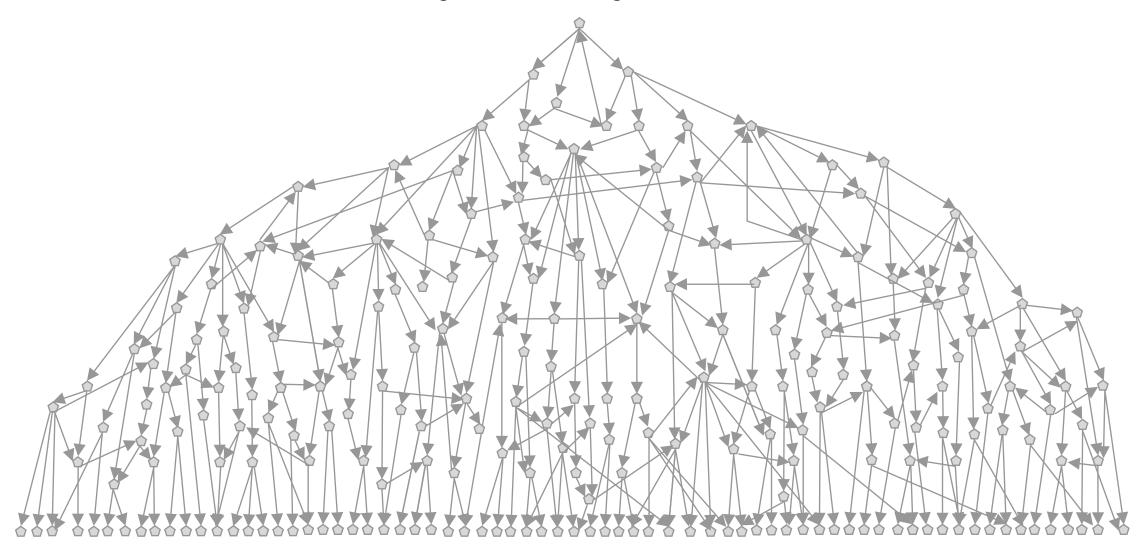


### **Conversations Move Back and Forth**



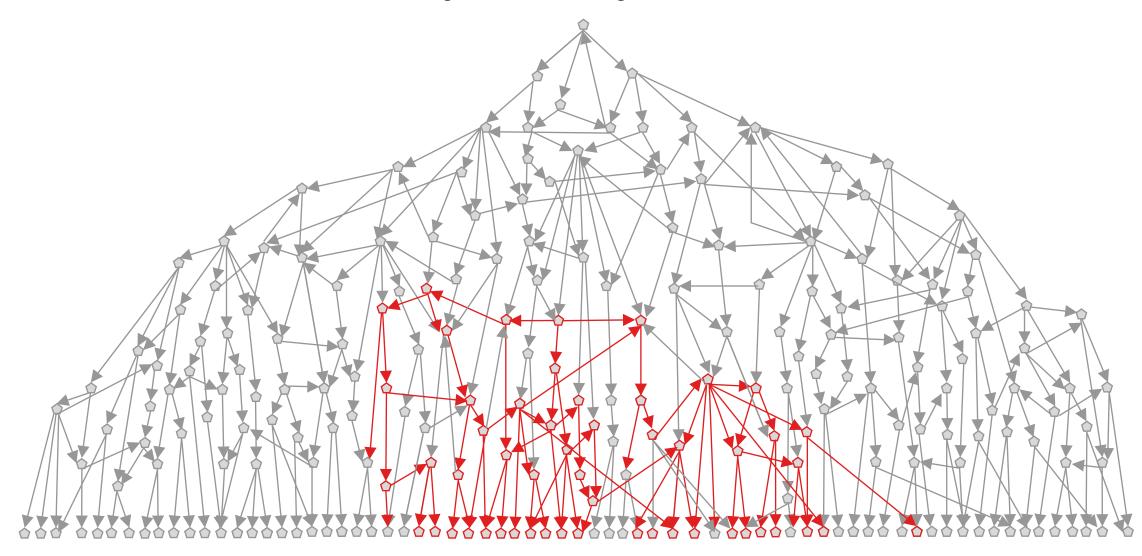
### Linear Conversations Get Complicated

But in real life, customers change their mind or give information in a different order



### So Updating Them is Over-Complicated and Expensive

But in real life, customers change their mind or give information in a different order



## **PolyAl Content Programming**

Logic trees (linear) = not scalable

Content Programming (non-linear) = scalable

### Creating Task-based Dialogue Systems

Convincing Application

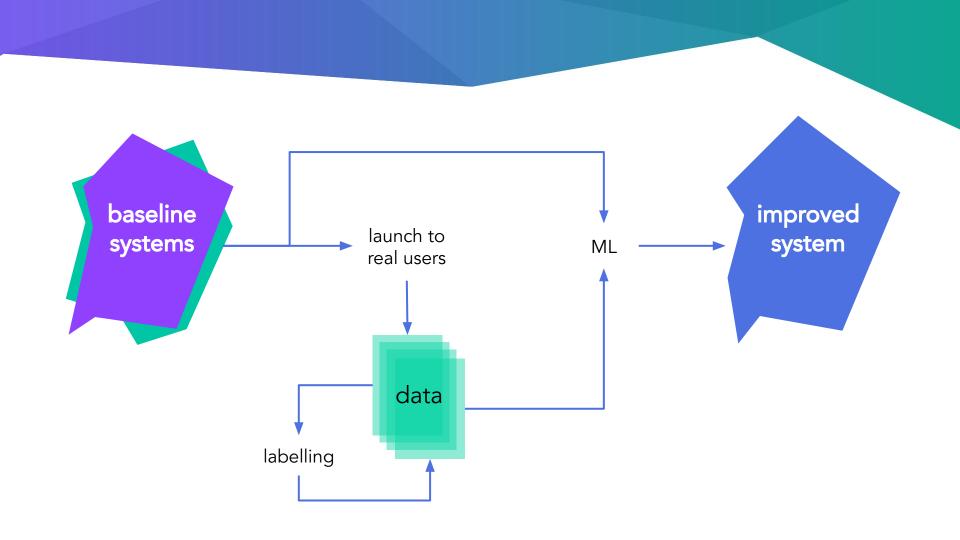
solves a real problem

Meaningful Evaluation

can measure progress

Annotaated Data

is machinelearnable



how do we get a

baseline system?

# 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

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.

. . .

- large conversational datasets

### Language Modelling

- large text datasets

- large conversational datasets
- representations encode conversational cues

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- encodes full sentences

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- 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

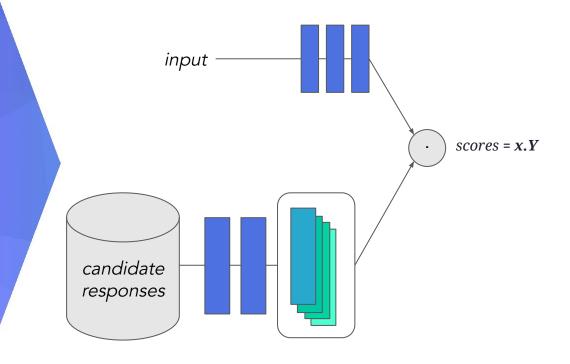
### Dual Encoders for Response Selection

dual encoder dot product model

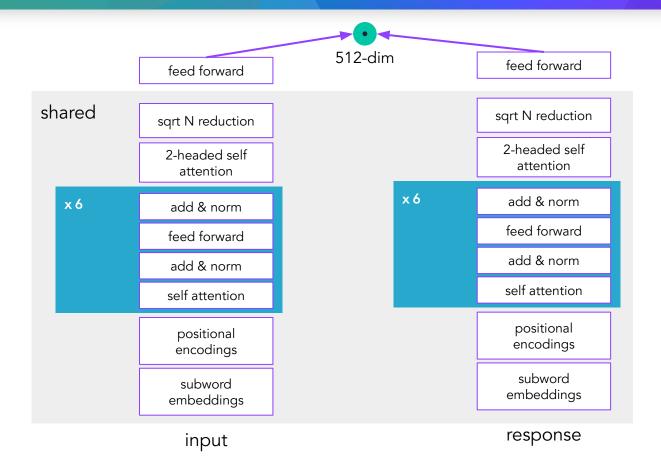
- gmail smart reply
- universal sentence encoder

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



### PolyAl Encoder



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:

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

$x_1, y_1$	$\boldsymbol{x}_1.\boldsymbol{y}_2$	$\boldsymbol{x}_1.\boldsymbol{y}_3$	$\boldsymbol{x}_1.\boldsymbol{y}_4$	$\boldsymbol{x}_1.\boldsymbol{y}_5$
$\boldsymbol{x}_2.\boldsymbol{y}_1$	$\boldsymbol{x}_2.\boldsymbol{y}_2$	$\boldsymbol{x}_2.\boldsymbol{y}_3$	$\boldsymbol{x}_2.\boldsymbol{y}_4$	$\boldsymbol{x}_2.\boldsymbol{y}_5$
$\boldsymbol{x}_3, \boldsymbol{y}_1$	$\boldsymbol{x}_3.\boldsymbol{y}_2$	$x_3y_3$	$\boldsymbol{x}_3.\boldsymbol{y}_4$	$\boldsymbol{x}_3.\boldsymbol{y}_5$
$x_4 y_1$	$\boldsymbol{x}_{4}.\boldsymbol{y}_{2}$	$\boldsymbol{x}_4, \boldsymbol{y}_3$	$x_4.y_4$	$\boldsymbol{x}_4.\boldsymbol{y}_5$
$\boldsymbol{x}_{5},\boldsymbol{y}_{1}$	$\boldsymbol{x}_{5}.\boldsymbol{y}_{2}$	$\boldsymbol{x}_{5}.\boldsymbol{y}_{3}$	$\boldsymbol{x}_5.\boldsymbol{y}_4$	$\boldsymbol{x}_5.\boldsymbol{y}_5$

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

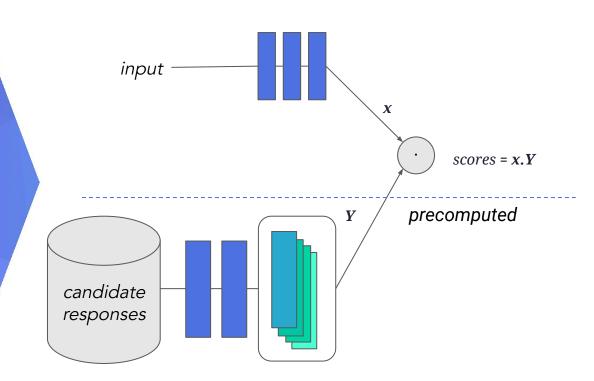
large improvement in 1 of 100 ranking accuracy over binary classification.

$x_1, y_1$	$\boldsymbol{x}_1.\boldsymbol{y}_2$	$\boldsymbol{x}_1,\boldsymbol{y}_3$	$\boldsymbol{x}_1.\boldsymbol{y}_4$	$\boldsymbol{x}_1.\boldsymbol{y}_5$
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$\boldsymbol{x}_3.\boldsymbol{y}_1$	$\boldsymbol{x}_3.\boldsymbol{y}_2$	$x_3y_3$	$\boldsymbol{x}_3.\boldsymbol{y}_4$	$\boldsymbol{x}_3.\boldsymbol{y}_5$
$x_4.y_1$	$\boldsymbol{x}_4.\boldsymbol{y}_2$	$\boldsymbol{x}_4.\boldsymbol{y}_3$	$x_4.y_4$	$\boldsymbol{x}_4.\boldsymbol{y}_5$
$\boldsymbol{x}_5.\boldsymbol{y}_1$	$\boldsymbol{x}_{5}.\boldsymbol{y}_{2}$	$\boldsymbol{x}_{5},\boldsymbol{y}_{3}$	$\boldsymbol{x}_5.\boldsymbol{y}_4$	$\boldsymbol{x}_5.\boldsymbol{y}_5$

# 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

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

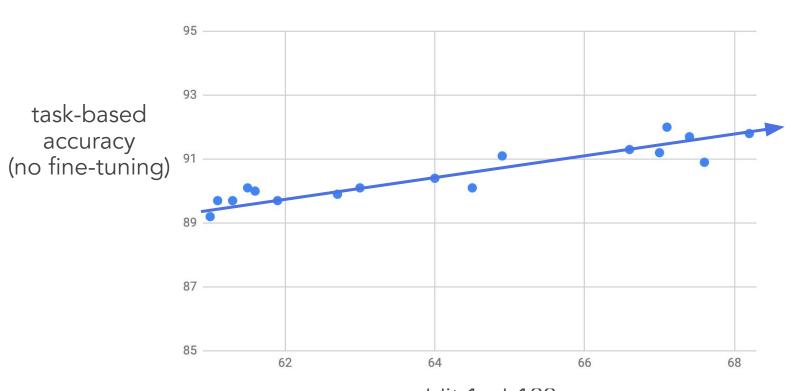
# PolyAl Encoder

	reddit 1-of-100		
		accuracy	
keyword-based	TF-IDF	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%	
	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)

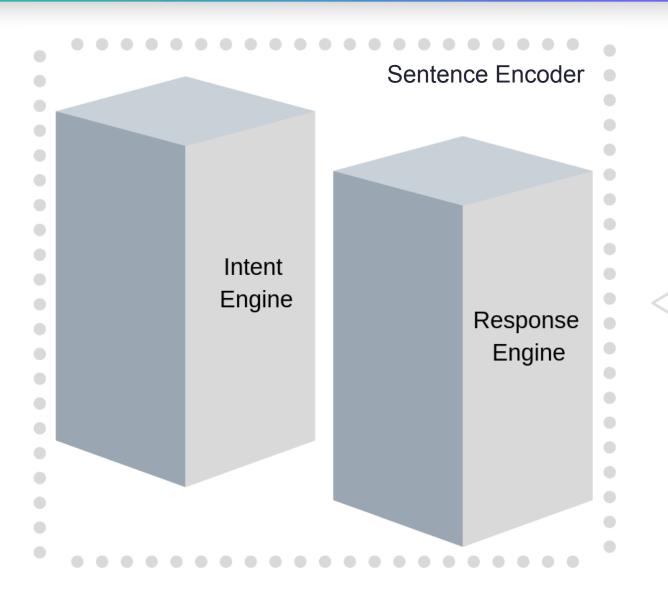
# Smart, Accurate Customer Service Solutions



Smart Call / Ticket Routing

Al-powered Agent Assistive Tool

Automated
Customer
Service Solution



Domain specific data

# 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

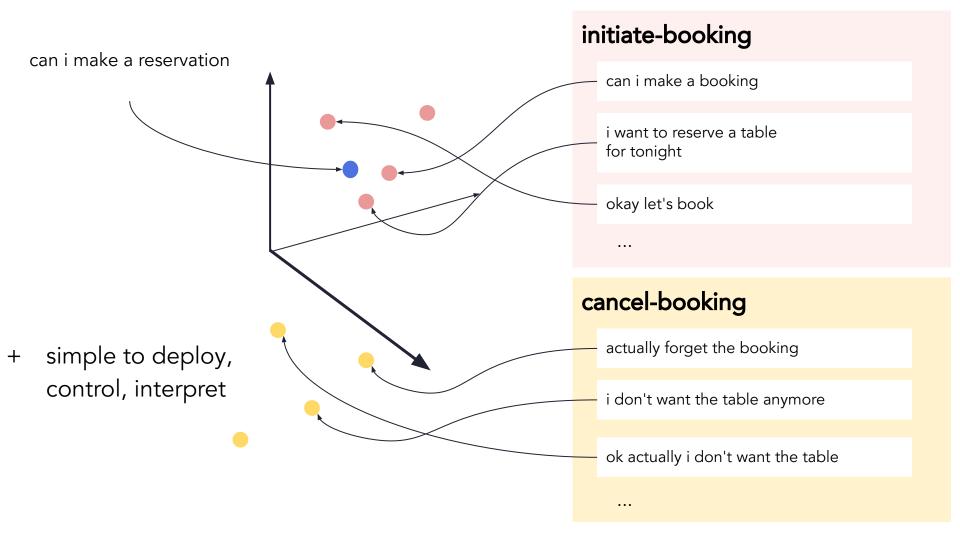
- can train an MLP on top of encoding representation
- can jointly fine-tune the encoding parameters

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

### Why is Out-of-the-Box Performance Important?

(Intent accuracy%)<sup>^number of turns</sup> = success rate of automation

 $(80\%)^{^2 \text{ turns}} = 64\% \text{ success rate}$ 



### Encoder Has Been Trained on Billions of Conversations

Jessep: You want answers?!

Kaffee: I want the truth!

Jessep: You can't handle the

truth!



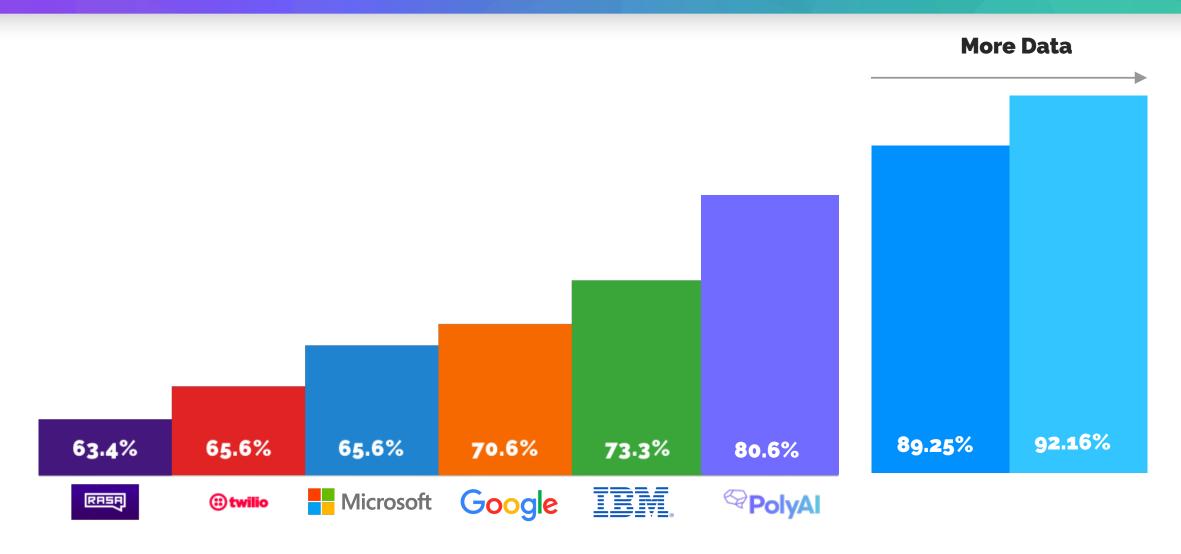


40 million lines of subtitles from film and TV

3.7 billion comments from online forums

3.6 million question/answer pairs from FAQ

# Poly Al Encoder: Better Performance Out-of-the-Box



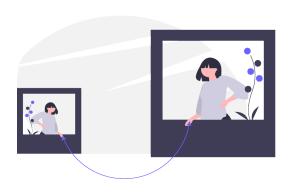
### The PolyAl Encoder: Understanding as a Service



Needs less data for deployment



Empower customers to speak naturally



Lightweight: MBs instead of GBs

# Intent Engine w/ Shared Representations

- I want an extra spicy one.
- Extra spicy chicken please.
- Extra hot, please.
- A pungent one, please.

. .



- Quiero uno extra picante.
- Pollo extra picante por favor.
- Extra caliente, por favor.
- Una picante, por favor.

...



- 나는 여분의 매운 것을 원한다
- 여분의 매운 닭고기주세요
- 아주 더워주세요
- 매운 것, 제발

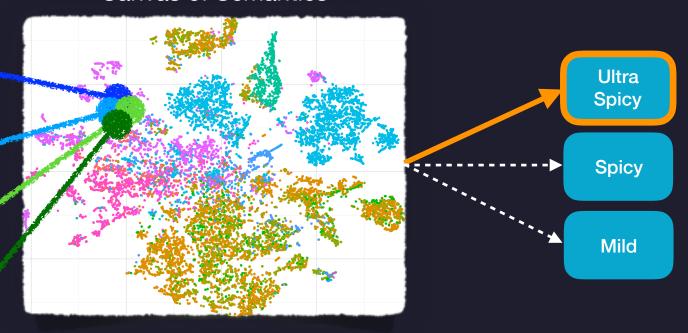
...



- 我想要特辣的
- 请给我一份特辣烤鸡
- 我吃很辣的
- 来一份大辣



### Canvas of Semantics



- Leverage public large datasets for generalization
- One model, multiple intents, many languages
- State-of-the-art performance comparing to other solutions

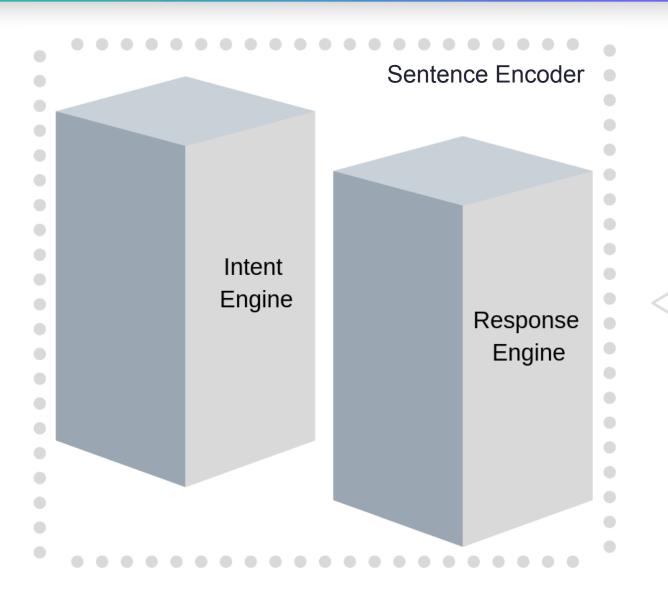
# Smart, Accurate Customer Service Solutions



Smart Call / Ticket Routing

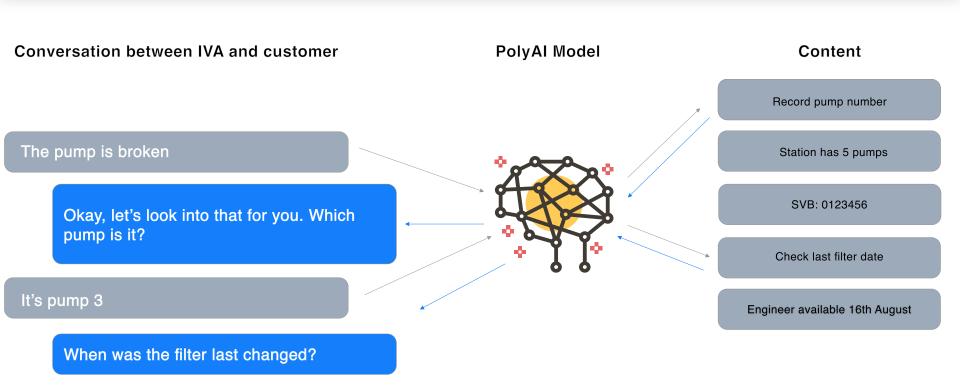
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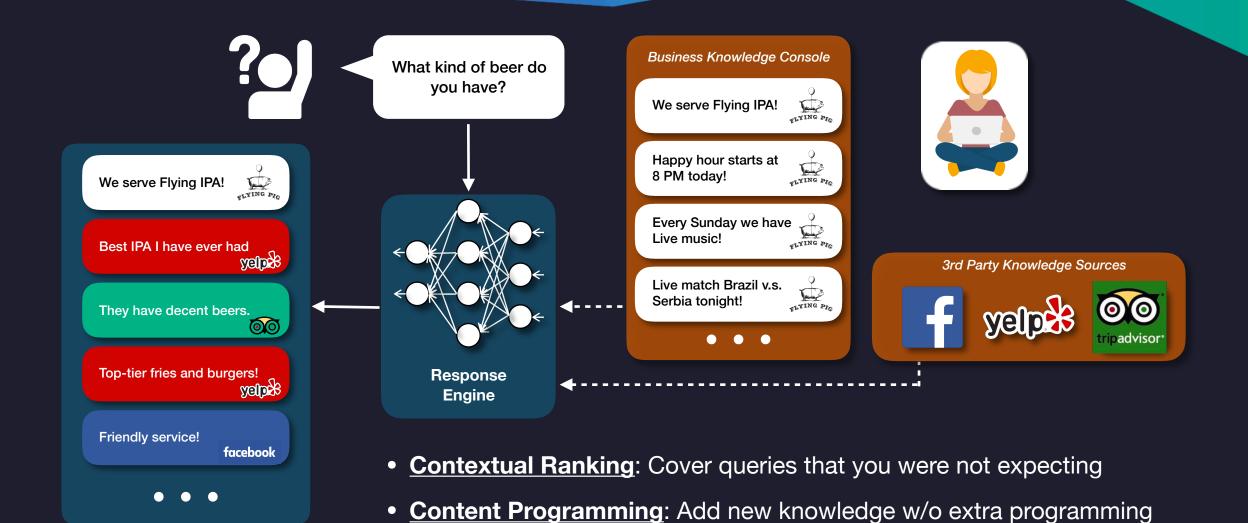


Domain specific data

### Giving the Best Answer at Every Turn



# Response Engine



**Business Logic Engine**: Build precise business logics on top

# 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**

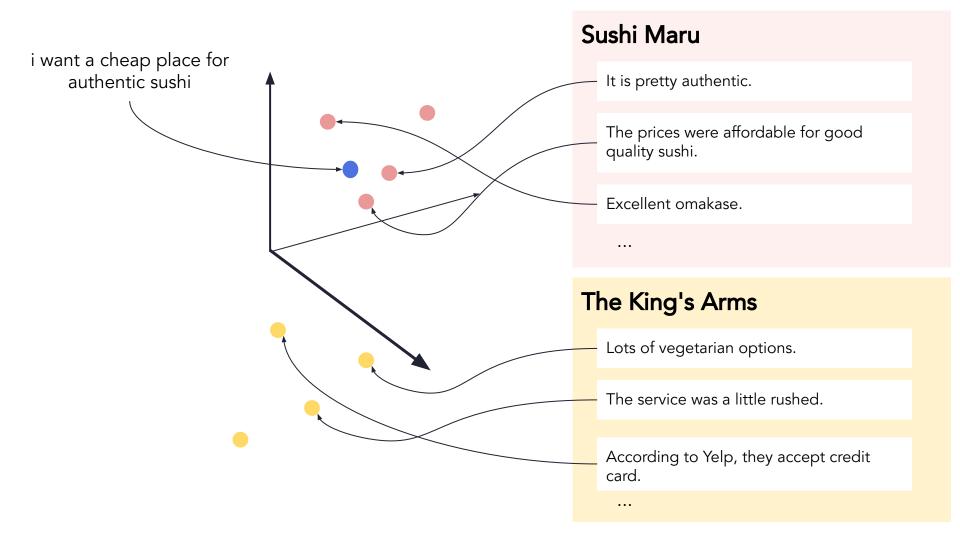
- some slots are necessary

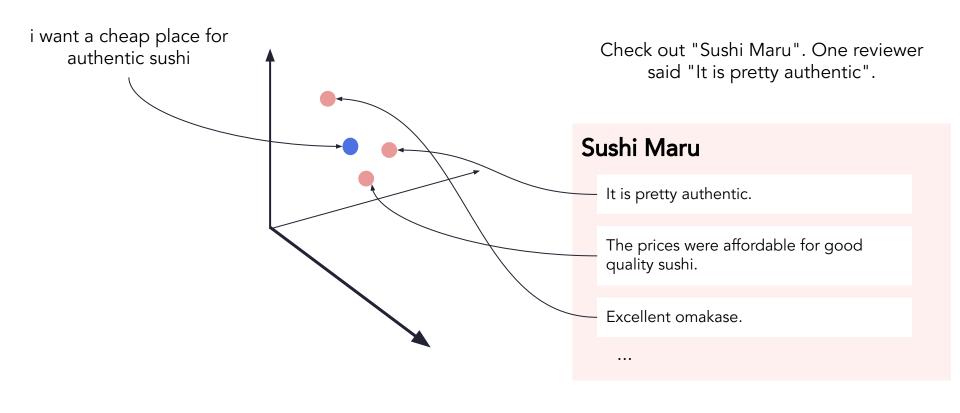
number of people, booking time, name

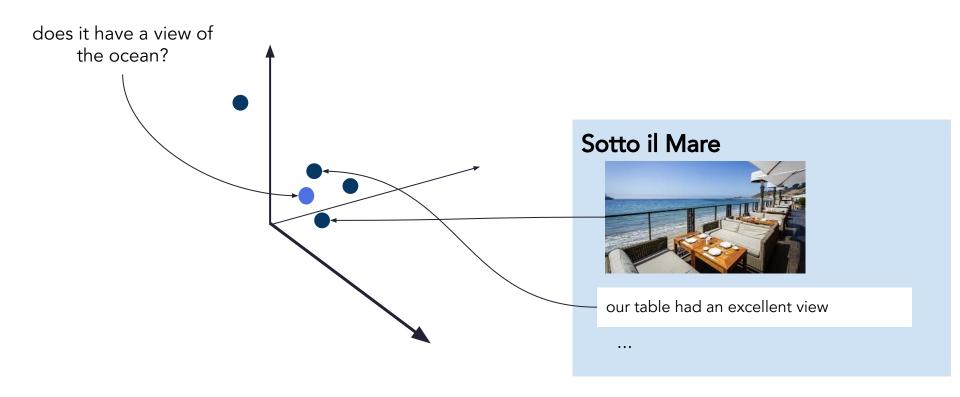
- some might not be

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







### The Elephant House

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

where did JK rowling write Harry Potter





• We got to see the spot where it is said JK Rowling wrote Harry Potter."

"So apparently JK Rowling often wrote Harry Potter here."

• "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?

### 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

### 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

# Live Demo



**Culinary Exploration of Edinburgh** 



