

The Conversational Enterprise

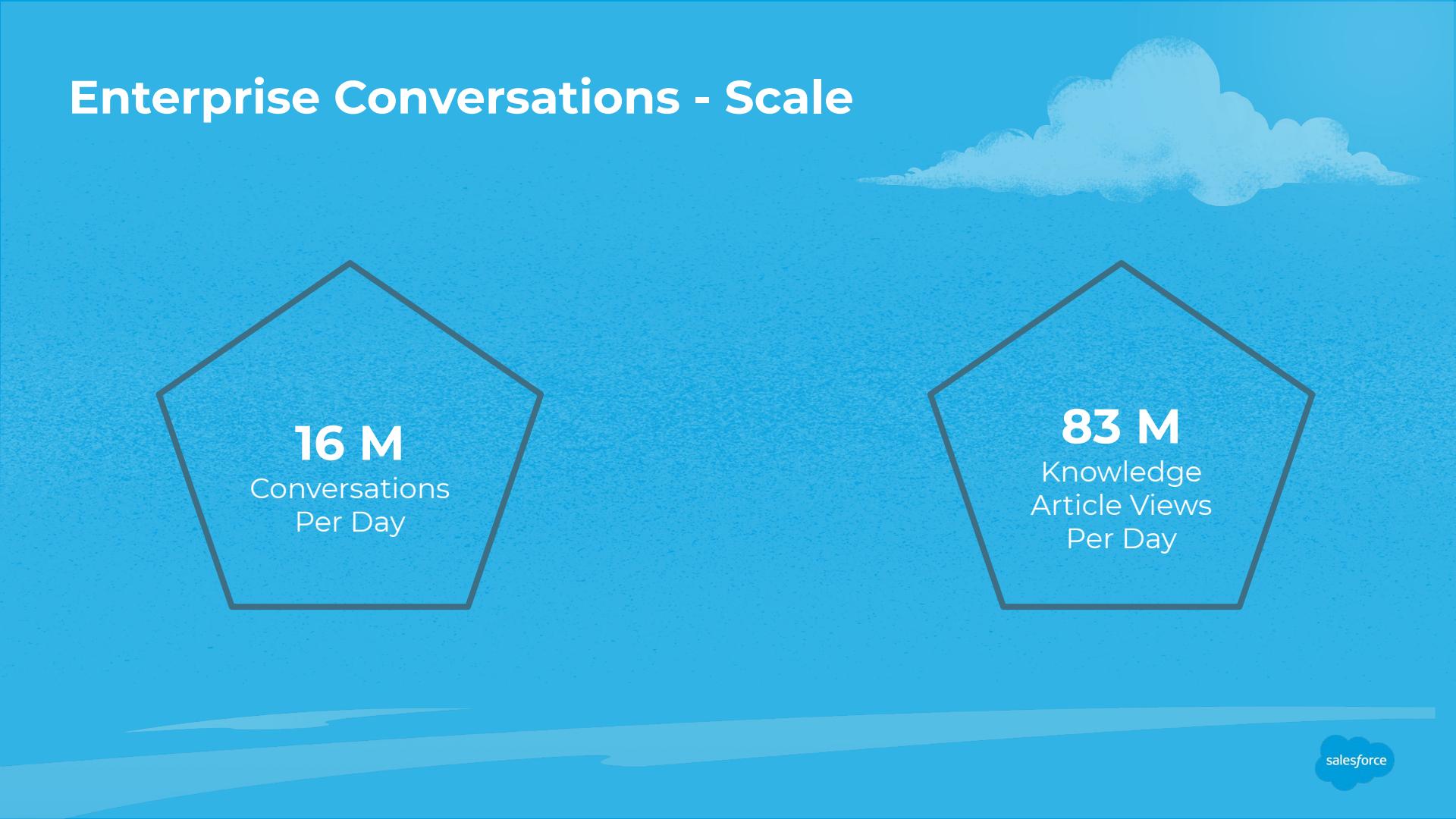
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VP Data Science, Engineering
Salesforce Einstein

Agenda

The Conversational Enterprise

1. Conversational user intent across industries
2. Service Conversations Archetypes
3. NLP and ML Systems in Customer Service
4. Deep Dive - A Simple conversational model (CM)
5. Leveraging CM to build an Response Recommender for Service Agents

Enterprise Conversations - Scale



16 M
Conversations
Per Day

83 M
Knowledge
Article Views
Per Day

Analyzing Service Interactions

/Conversational Intent by Industry

Industries

From all the industries Salesforce operates in we selected 5 industries. These represent a wide diversity in vocabulary coupled with a high volume of conversation:

1. Retail
2. Banking
3. Consumer Goods
4. Insurance
5. Cable and ISP

Learn how the world's #1 CRM solution helps you forge a path to success in your industry.



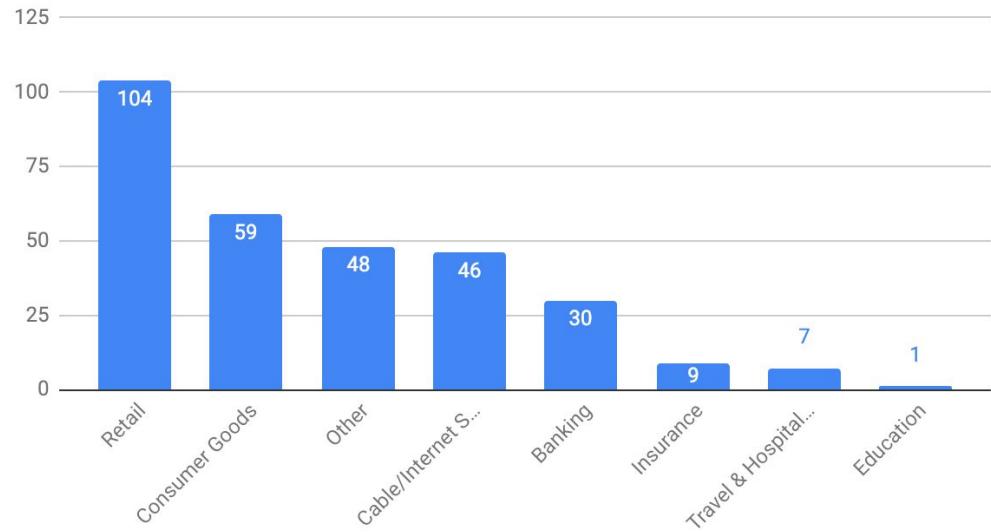
Service industry contacted

Participants selected from 5 industries:

1. Retail
2. Banking
3. Consumer Goods
4. Insurance
5. Cable and ISP

The most common industry for which participants engaged customer support via chat was **retail**, indicating the value of conversational AI in this space.

Service Industry Participant Contacted



N = 304



What We Found (in order of frequency)

Retail

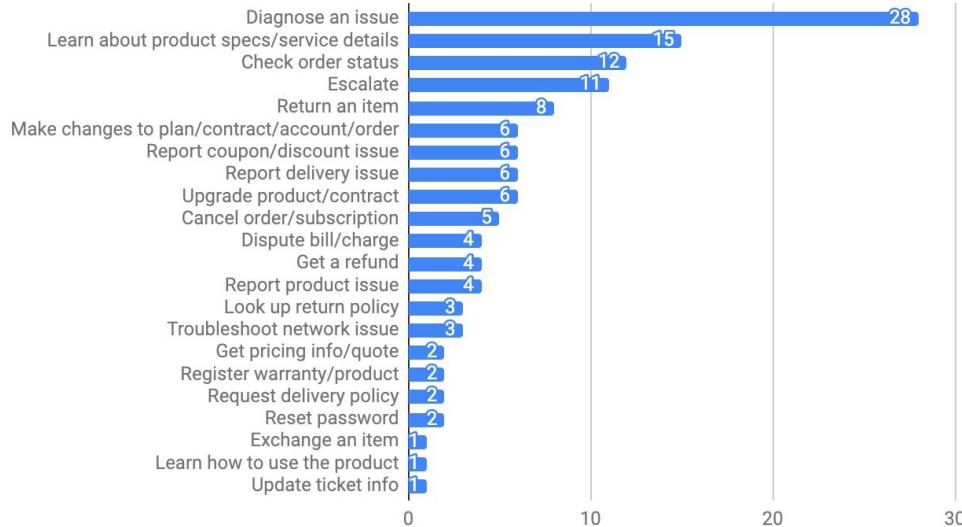
1. Learn about product specs/service details (34)
2. Check order status (25)
3. Return an item (23)



N = 103
Total Mentions = 191

Consumer Goods

1. Diagnose an issue (28)*
2. Learn about product specs/service details (15)
3. Check order status (12)



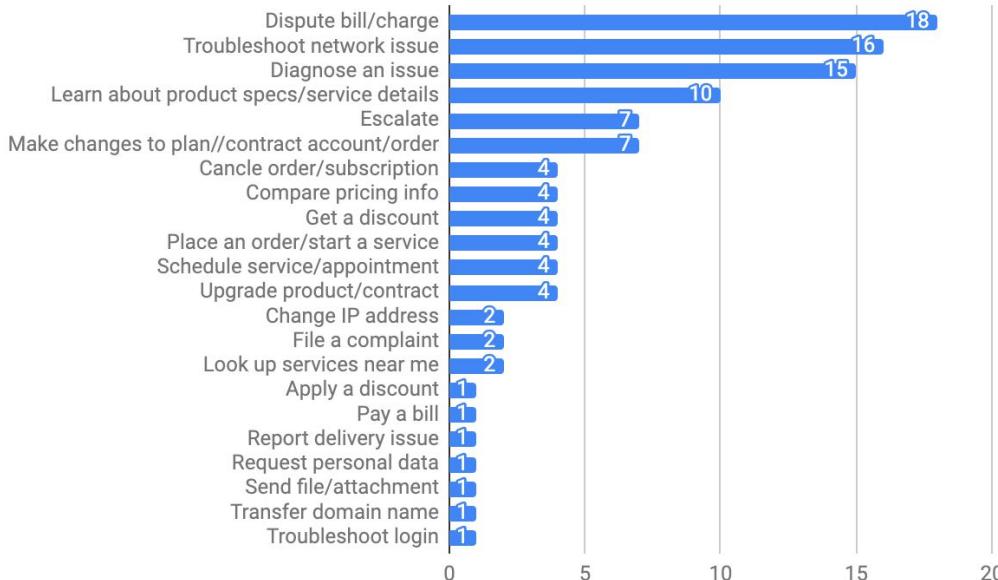
N = 60

Total Mentions = 130



Cable & ISP

1. Dispute bill/charge (18)
2. Troubleshoot network issue (16)*
3. Diagnose an issue (15)



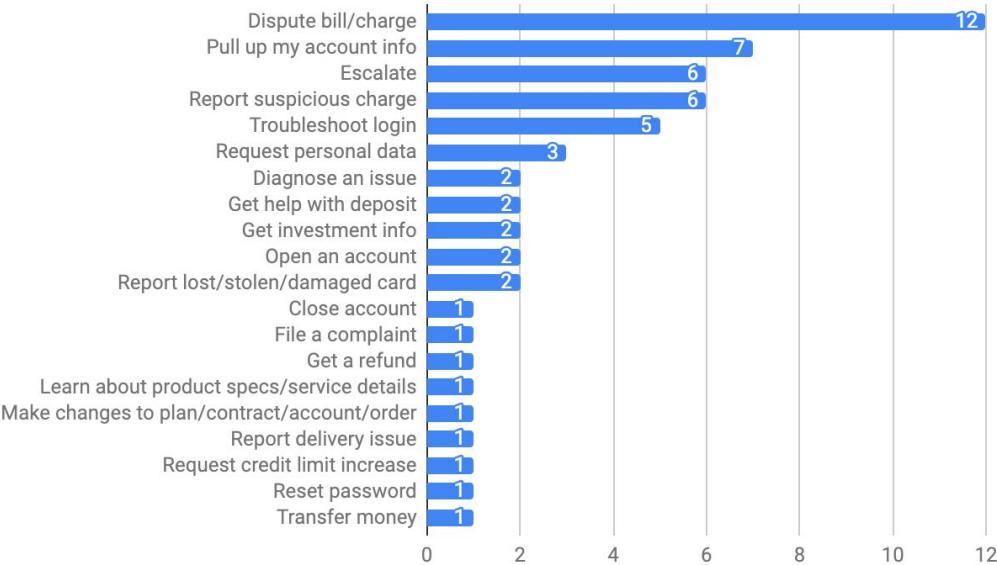
N = 47

Total Mentions = 110



Banking

1. Dispute charge (12)
2. Pull up my account info (7)
3. Escalate (6)
- Report suspicious charge (6)



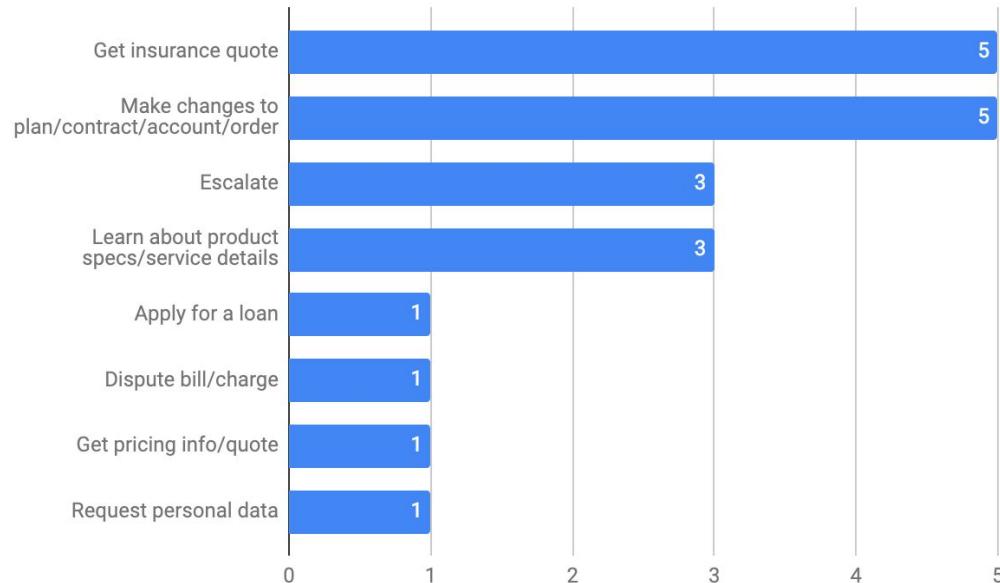
N = 30

Total Mentions = 58



Insurance

1. Get insurance quote (5)
2. Make changes to plan/contract/account/order (5)
3. Escalate (3), Learn about product specs/service details (3)

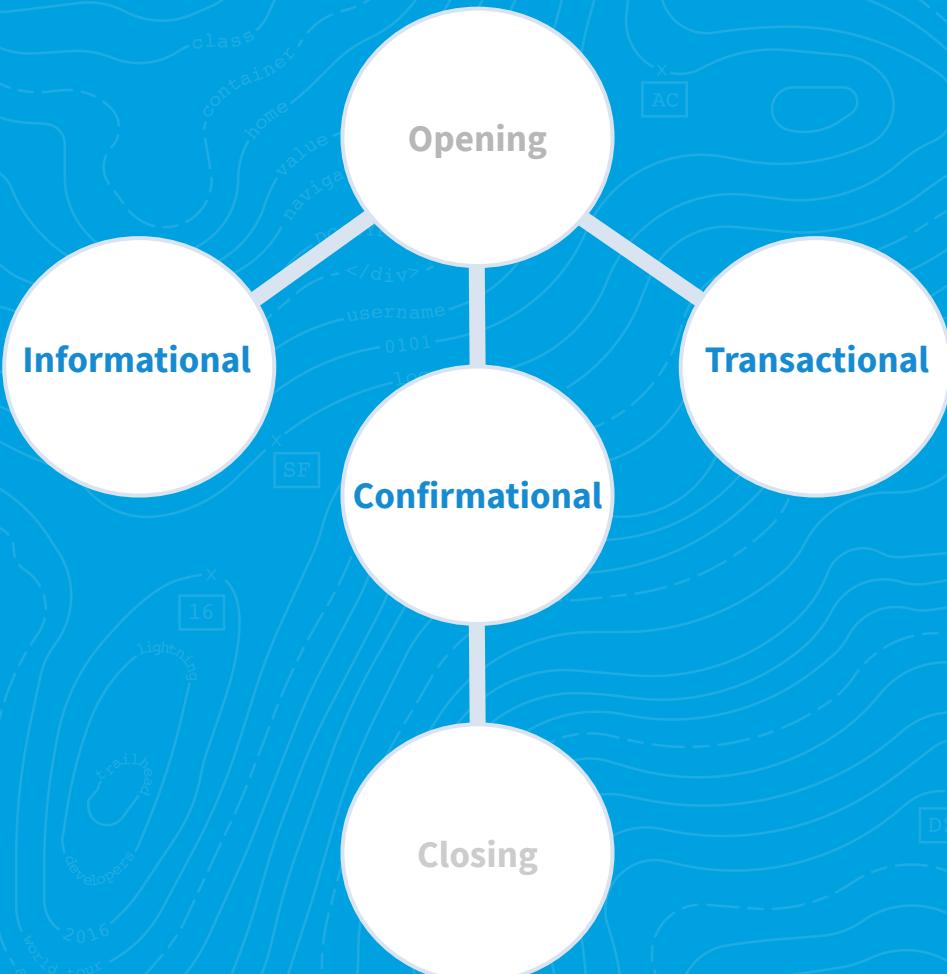


N = 9
Total Mentions = 20


Service Conversation Archetypes

/We discovered types of customer requests

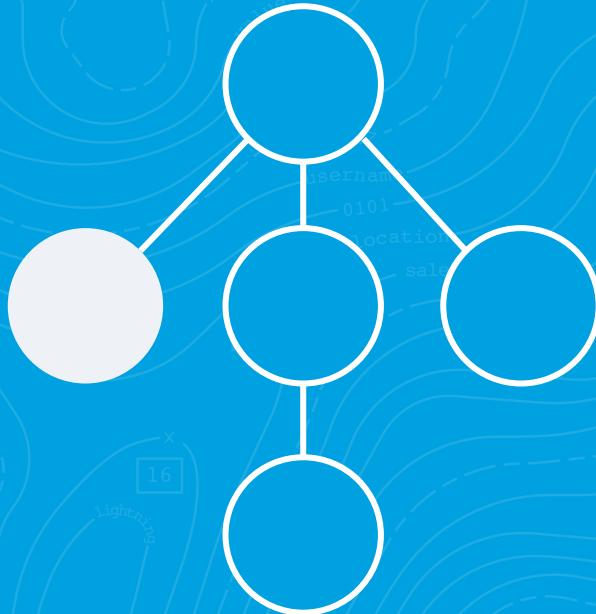
CUSTOMER REQUEST ARCHETYPES



Conversation begins

Customer makes a request (this is the **Intent**)

Conversation ends



1. Informational

Customer wants to learn or obtain new information.

“What is the baggage limit on SFO- DEN flights ?”
“What is the return policy on my purchases ?”
“How much warranty do I have left on my device?”

2. Confirmational

Customer has some info and wants to confirm its validity.

“Am I eligible for an upgrade?”

“I’d like to confirm my flight booking for Denver to LA.”

“Has my order already been shipped?”

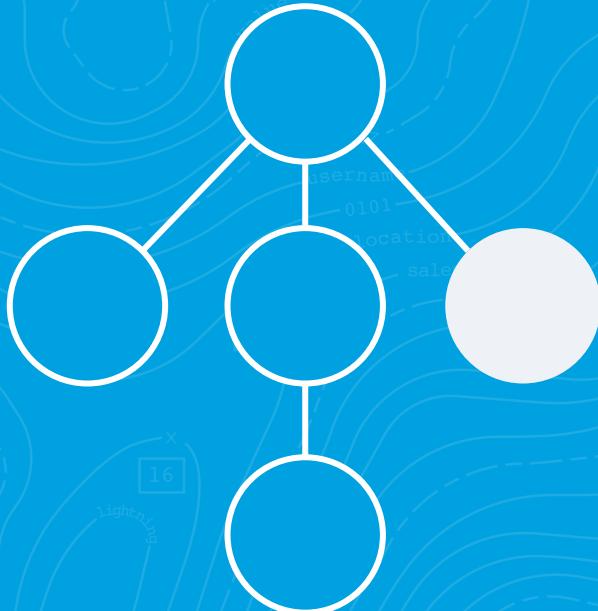
3. Transactional

Customer requests action be taken.

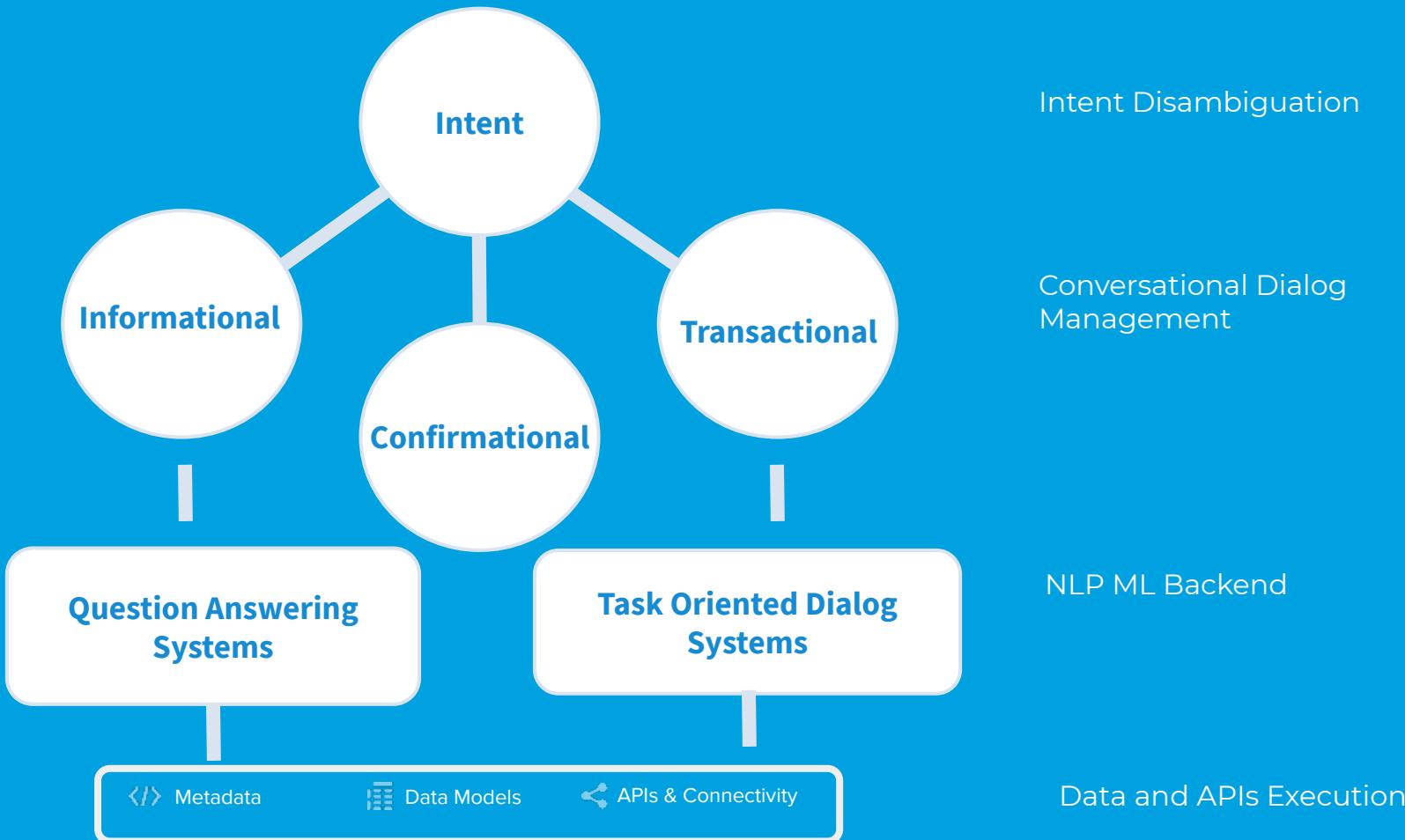
“The shirt I received is too big.”

“I’m trying to return the speakers I ordered.”

“I just moved apartments. Can you change my billing address?”

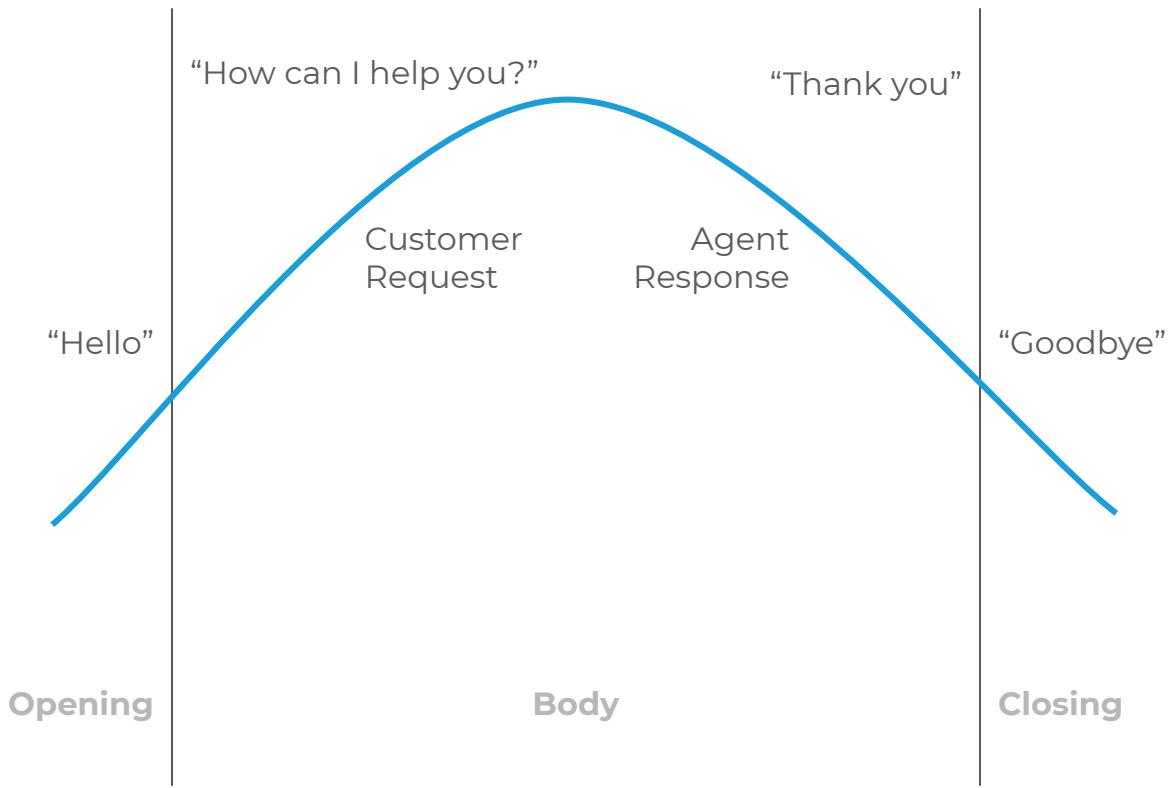


SYSTEMS

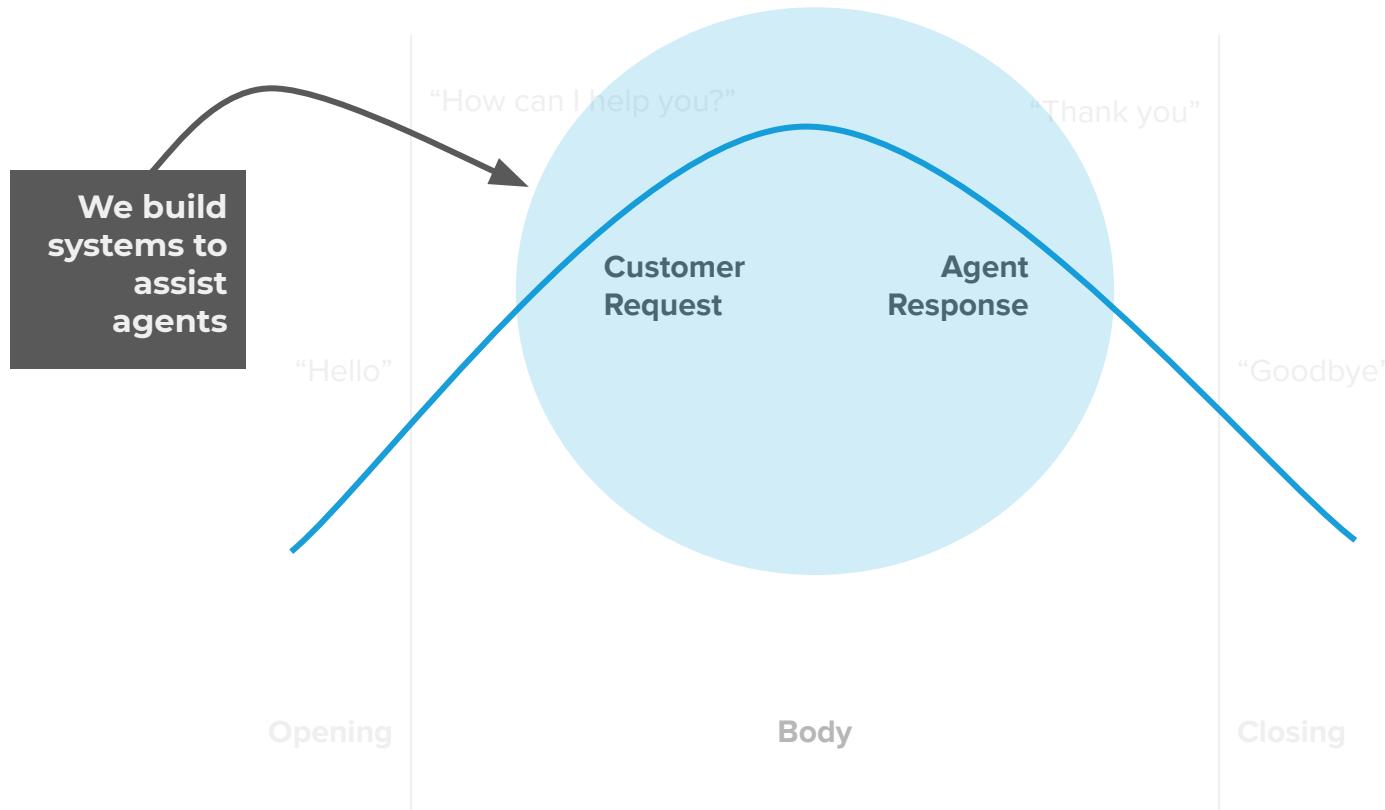


NLP and ML in Customer Service Agent-Assist

CANONICAL STRUCTURE OF A CUSTOMER <>> SERVICE AGENT CONVERSATION



CANONICAL STRUCTURE OF A CUSTOMER SERVICE CONVERSATION



ASSIST AGENTS' WORKFLOW

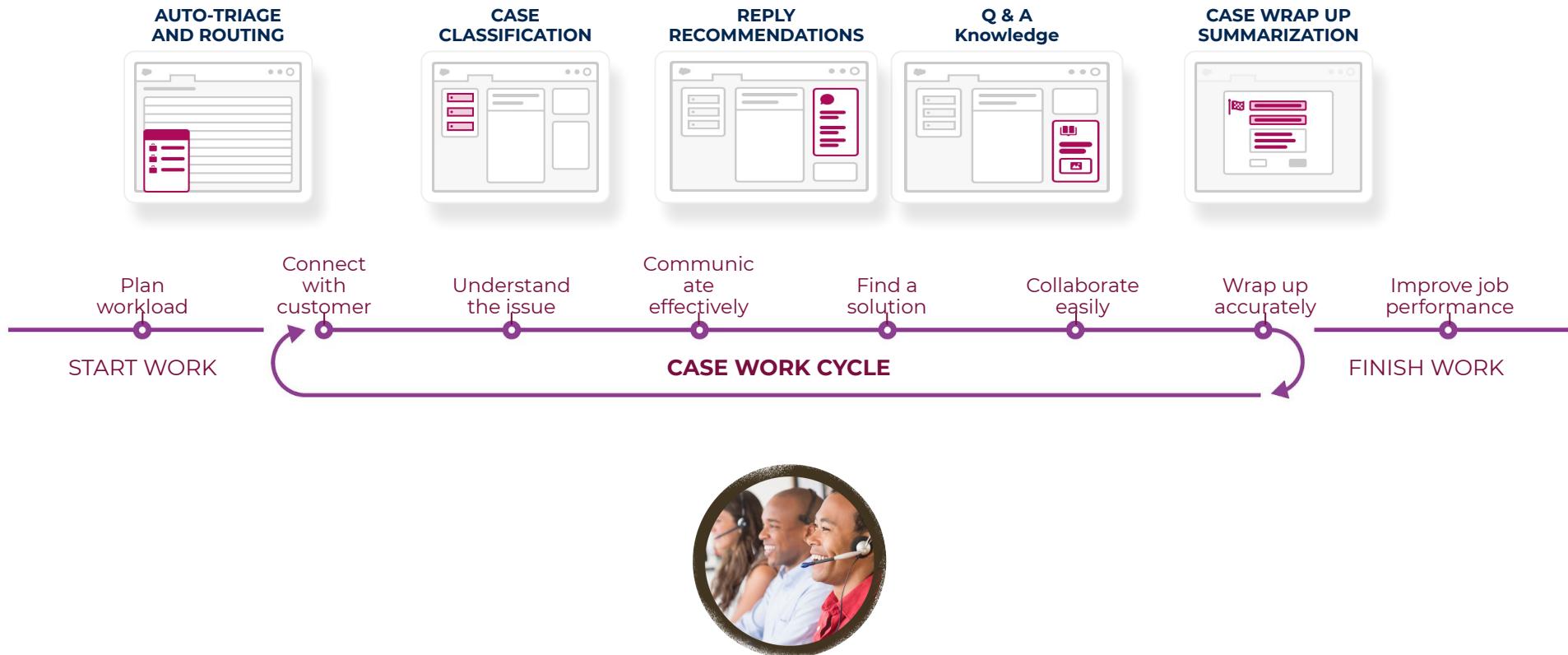
Orchestrate

Compose

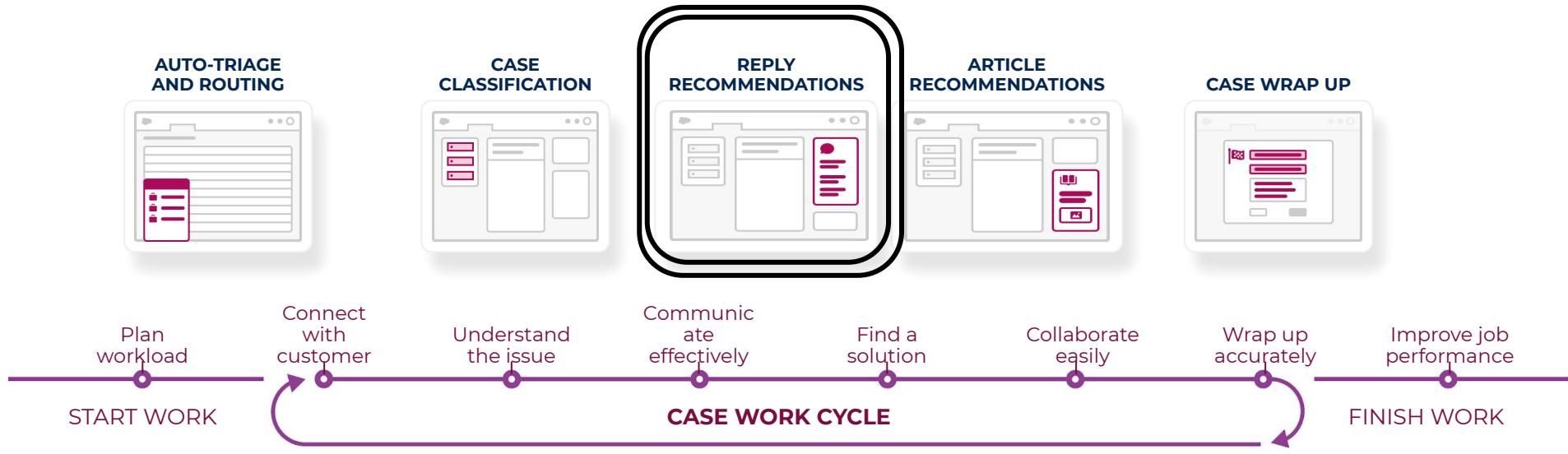
Collaborate



ASSIST AGENTS' WORKFLOW



ASSIST AGENTS' WORKFLOW



Reply Recommendations



- Agent assist (as opposed to automate)
- In the context of chat conversations, suggest common responses for the agent to enter directly into the chat.
- Save the agent from having to type the same “return policy” response over and over again....



Contact Detail

Name Phone
Candace Ward (706) 951-2272

Email
Candace.Ward@gmail.com

Location
1401 Oakridge Lane, Augusta, GA 30901

Chat Transcript Details

Name Status
Candace Ward In Progress

Owner
Jesse Richmond

Request Time
1/4/2017 at 4:59 PM

Customer Orders

Order Detail **BZR01116491**

Name Phone
Candace Ward (706) 951-2272

Email
Candace.Ward@gmail.com

Shipping Address
1401 Oakridge Lane, Augusta, GA 30901

[Re-send Return Label](#)

Hello, I was trying to return 2 items but it's not allowing me to do so online

CHAT DETAILS

Hello, I was trying to return my order but it's not allowing me to do so online. i get a "site maintenance error"

Candace Ward · 5:00 PM

Just one moment please, while I look up your order.

Jesse Richmond · 5:02 PM

OK

Candace Ward · 5:03 PM

Responses

5:03 PM

BEST [Return Label How-To](#) · Confidence 95%

A return label has been sent to your email. Please print out the return label. Put the item(s) in its original packaging and apply the return label at the back of the box. Take the package to a shipping location and drop it off.

[Post in Chat](#) [Personalize](#) [Dismiss](#)

[Return Policy](#) · Confidence 91%

You can return your purchases made online through our website or at one of our stores. You can return items within 30 days, in unused condition.

[Post in Chat](#) [Personalize](#) [Dismiss](#)

[Return FAQ](#) · Confidence 88%

Once your return has been received and processed you will receive a refund in 7 to 10 days in the same method of payment that you purchased the item

[Post in Chat](#) [Personalize](#) [Dismiss](#)

[Return FAQ](#) · Confidence 88%

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Etiam porta, elit eget mollis imperdiet, magna ante luctus ipsum, vitae convallis sem turpis ac sapien. Proin semper libero augue, at suscipit odio consectetur vel. Nulla imperdiet non sapien quis laoreet. Proin



End Chat

Type a message...



Call



Macros



History



Notes



Omni-Channel

Product Considerations



- **Must be applicable across all archetypes**
 - Informational, Confirmational, Transactional
- **Minimal risk**
 - Responses should be retrieved rather than generated.
- **Dynamic and Personalizable.**
 - Agents prefer to speak in their own voice.
 - Each agent should be able to personalize their predefined response list.
 - Agents should be able to edit their lists whenever they want.
- **Easy setup**
 - Ideally, customers should be able to 'just turn it on'

Reply Recommendations Flow



1. Customer turns on the feature
 - a. Build a model using historical chat transcripts.
2. (Optional) Admin Setup
 - a. Admin manually creates a list of 'good' canned responses. These are global responses, available to all agents.
3. Each agent curates their own list
 - a. Right-click "add to list" after typing a response.
 - b. Model suggests responses in real time that should be added to the list. (After the agent has already typed the response)
4. Model recommends responses from the canned response lists.

Training Data



Agent: Hi, I'm <name> and I will be assisting you today!

Customer: Hello I was just wondering when my <items> would be shipped

Customer: Do you need my order number?

Agent: I apologize for the inconvenience regarding your delivery. I'd be more than happy to provide you with an order status.

Agent: Yes can you provide me with you Reference number

Customer: <PII>

Agent: And also can you verify your full name and email address for me?

Customer: <PII>

Customer: <PII>

Agent: Thanks! Your order was released for warehousing today. All of our orders must go through a processing period which takes up to 1-3 business days.

Customer: So it's being shipped today?

Agent: Yes, since you placed your order on the <date>, your order will be shipped by the end of the day today and you will be receiving a tracking number by today or tomorrow.

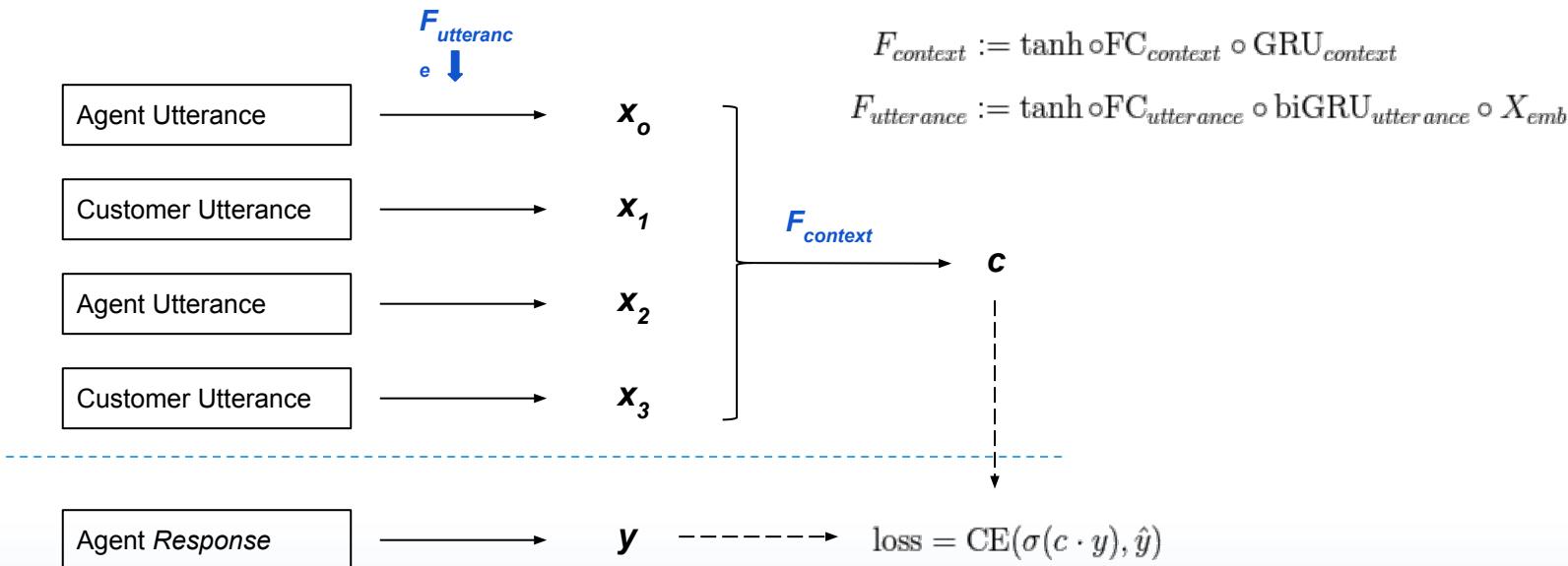
Customer: Okay thank you

Agent: Your welcome! Can I help you with anything else?

Training data consists of 10s of thousands of such chats (filtered for length, language, etc.)

Model

Hierarchical Siamese GRU



One training example consists of one partial conversation and either the true agent's response, or a randomly sampled agent response.

Model Serving

Prediction



Off-core AWS

Pre-compute

User Defined
Canned
Responses

Serving Container

Pre-compute response vectors (TF)

Response

Response
Embedding:
 $F(response)$

Vectors Stored On-Core

User-defined
Canned Response
Vectors

RunTime compute 800ms

LiveChat in
progress

Parse / Tokenize

Compute query vector (TF)

Context (partial
conversation)

Context
Embedding:
 $G(context)$

Similarity Score =
 $H(F, G)$

$O(n)$

Top K Responses

Evaluation



- Performance on the training task
 - AUC
 - Acuity
- Performance in production
 - Precision / Recall
- Offline heuristics
 - Does the model appear to work well on historical chats?

Training Performance

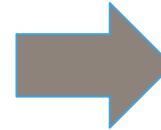


Customer 1 - 10 epochs

- AUC: 0.986
- Acuity: 0.979

Customer 2-30 epochs

- AUC: 0.966
- Acuity: 0.966



Green light!

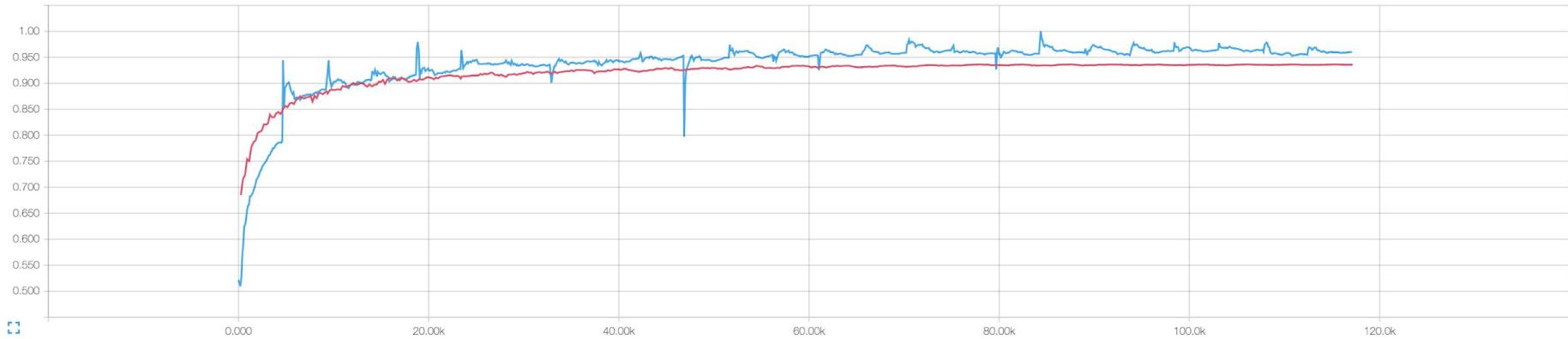
Rough calculation of human-level performance on
the training task is on the order of 95% accuracy

*Acuity := $P(\text{score of true response} > \text{score of random response})$

Training Curve



AUC



Recap

The Conversational Enterprise

1. Customer conversations topically diverse across industries
2. 3 Conversational Archetypes in Customer Service
3. Sophisticated systems that blend Q&A, Goal oriented dialog system and Conversational Models are needed to enable AI in customer service
4. Human in the loop Agent Assistive applications are a good starting point



Thank you.

We are Hiring!