How May I Help You?

Improving the Online Customer Experience Using Machine Learning

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Business Partners

AT&T Technical Development

Chat Operations

Digital Customer Service

Tools and Technology Strategy

Customer Experience Evaluation

Outline

Motivation

Impact of Transfers

Challenges of existing environment

New Approaches

- Address business goals
- Modeling and System

Results

Next Steps

Motivation : Live Chat as a Care Channel and Finding a Best Agent

AT&T had more than 21 million online chat sessions in 2016 (att.com 2017)

Chat volume is expected to grow:
More customers choose chat over traditional care channels

Migration to chat :
Potential cost savings in operational expenses

Chat Benefits Depend on Optimal Routing

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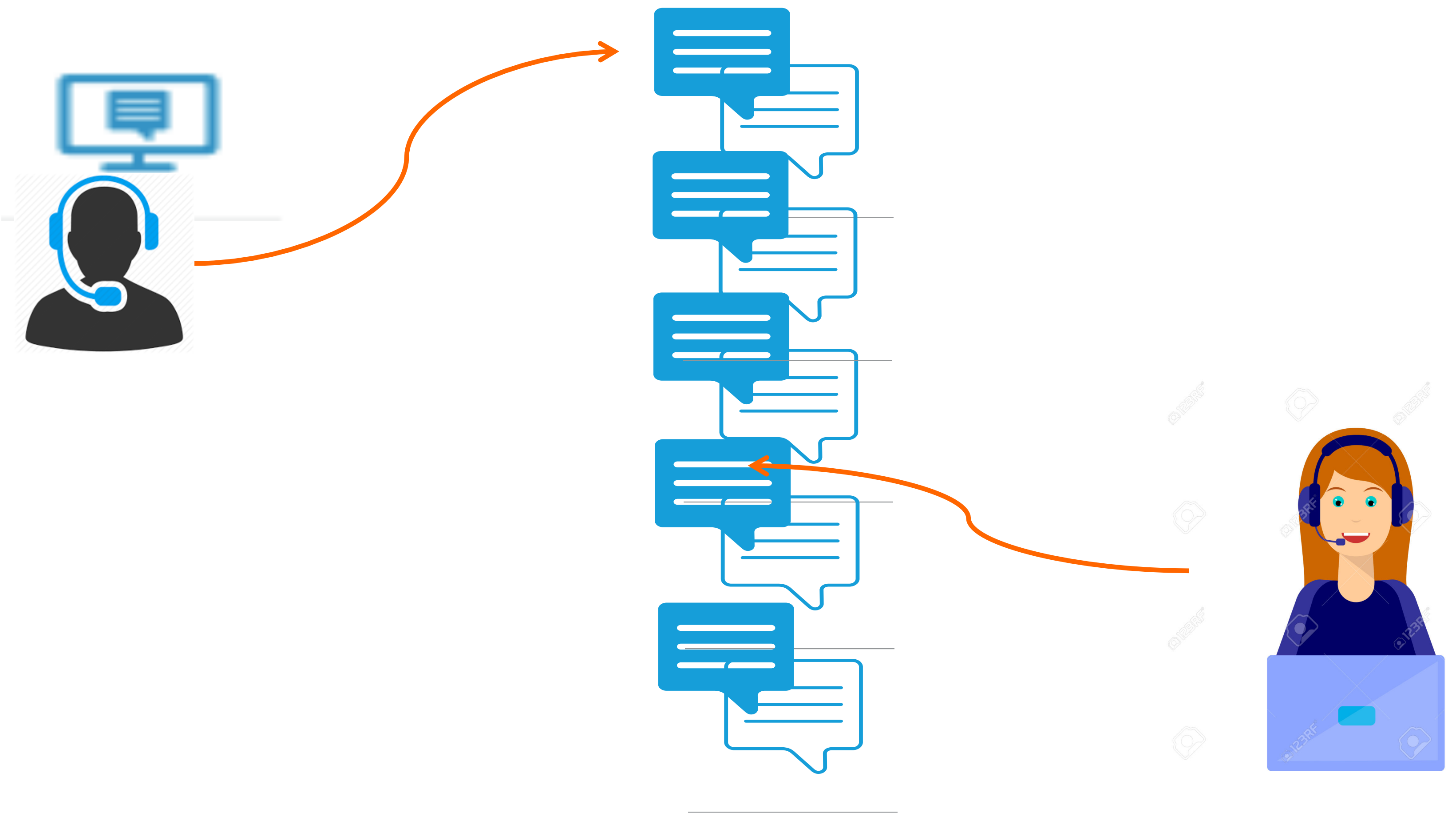
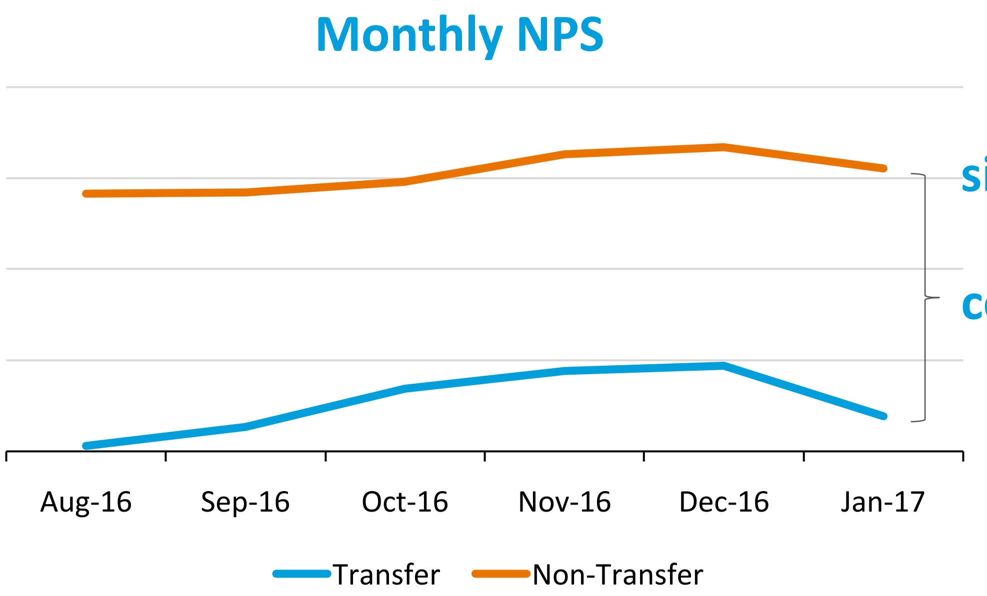
Incorrect Routing -> Transfer



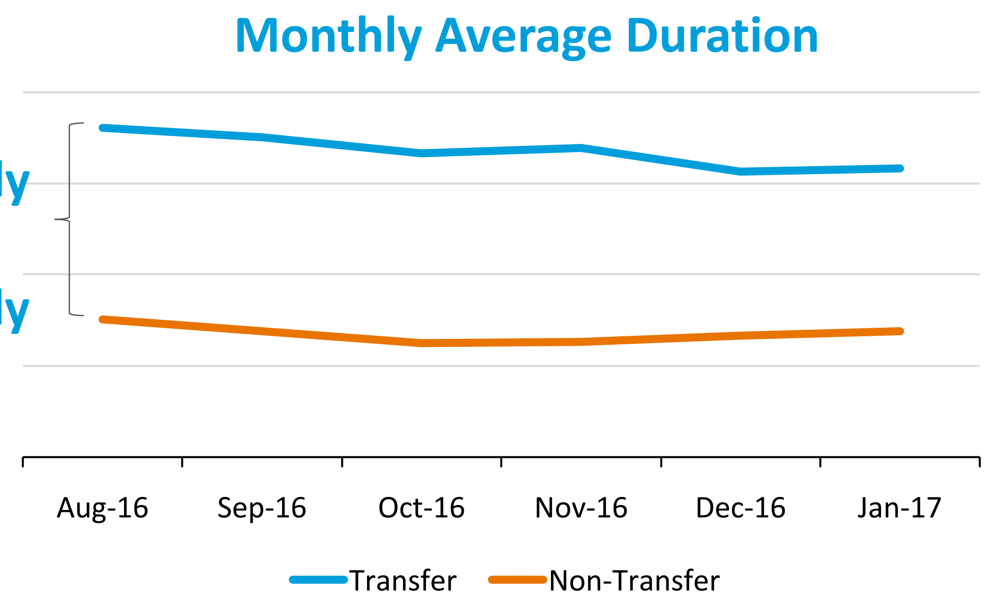
Impact of Transfer

Transfers negatively impact NPS scores



significantly and consistently lower

Transfers increase interaction duration



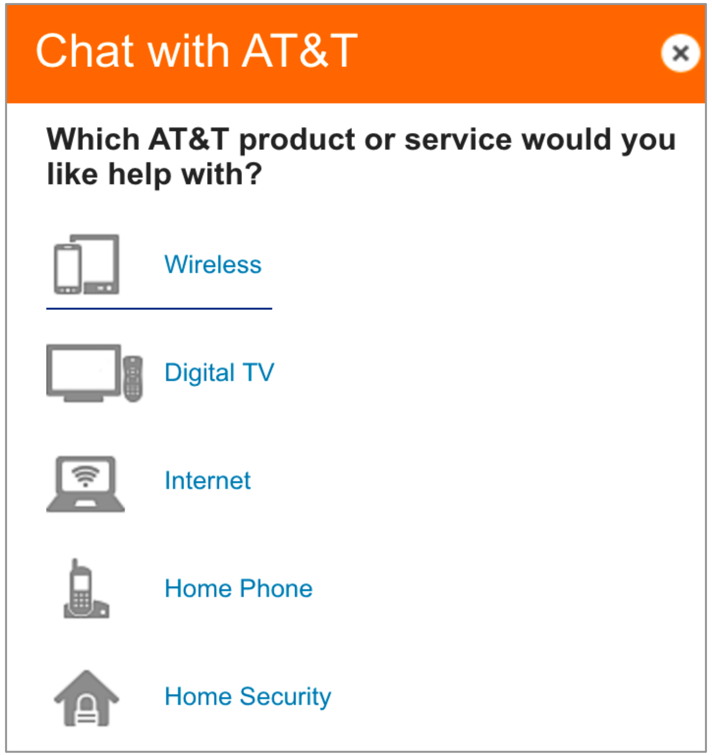
Reducing transfers due to incorrect routing will improve customer satisfaction and reduce costs driven by the increased chat time.

Existing Customer Experience

Asked to make a series of menu guide selections

Customer launches chat from att.com webpage

Chat available



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Customer routed to agent based on menu selections, launch page, and clickstream

Challenge

- **Deterministic, needs frequent monitoring**
- **Customer's navigation path reflects self-initiated search path for answers**
- **Customer's true, detailed intent is not revealed until the conversation starts**

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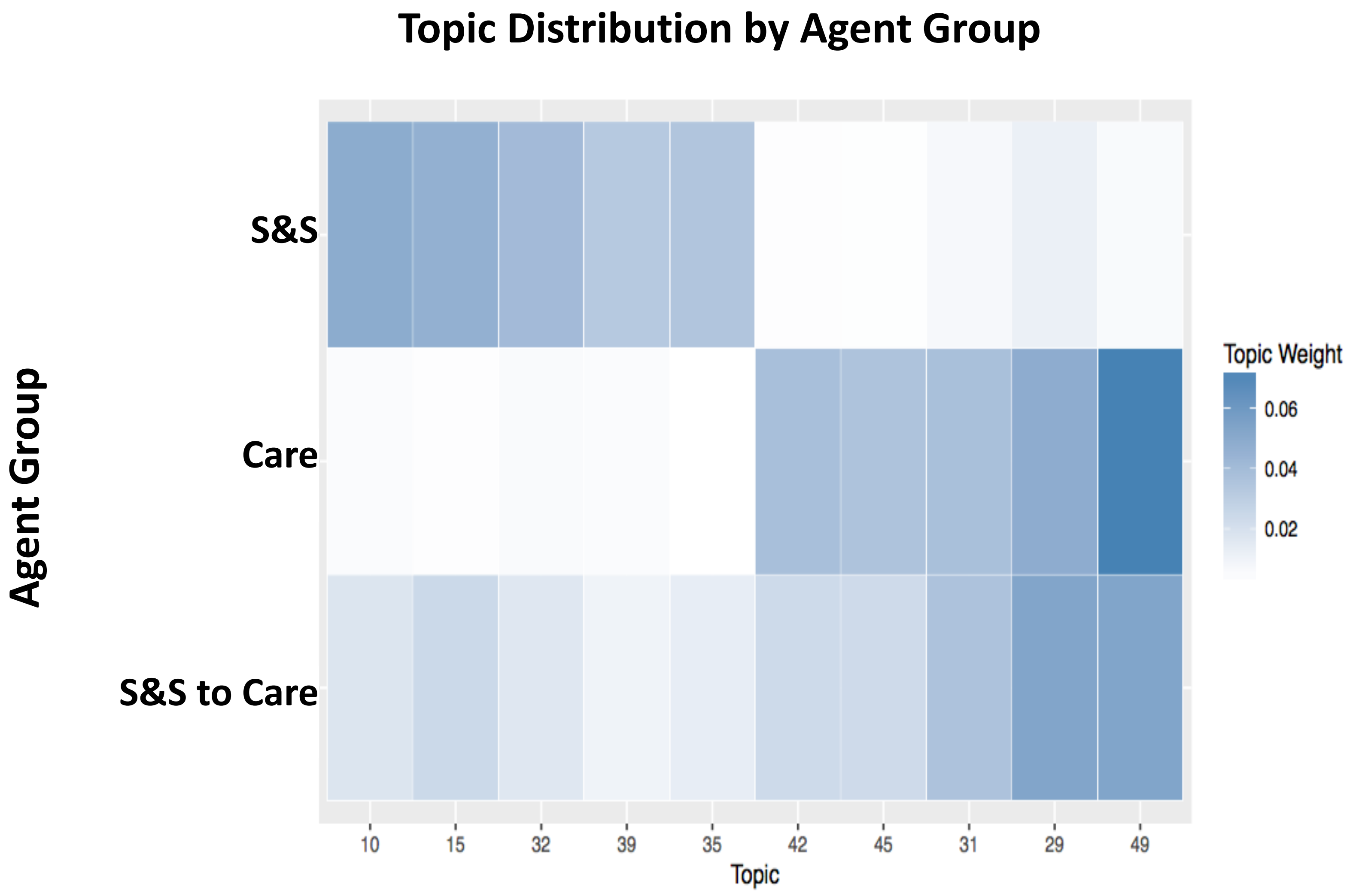
Evidence of Intent Mismatch

- Intent: reason for inquiry, use initial customer turns of two agent groups
- Comparing non-transfer and transfer chats
- Chats transferred from Sales & Services to Care mention issues handled by Care more often than non-transferred chats.
- Using features designed to reveal intent mismatch, we can build a model to detect transfers with high accuracy

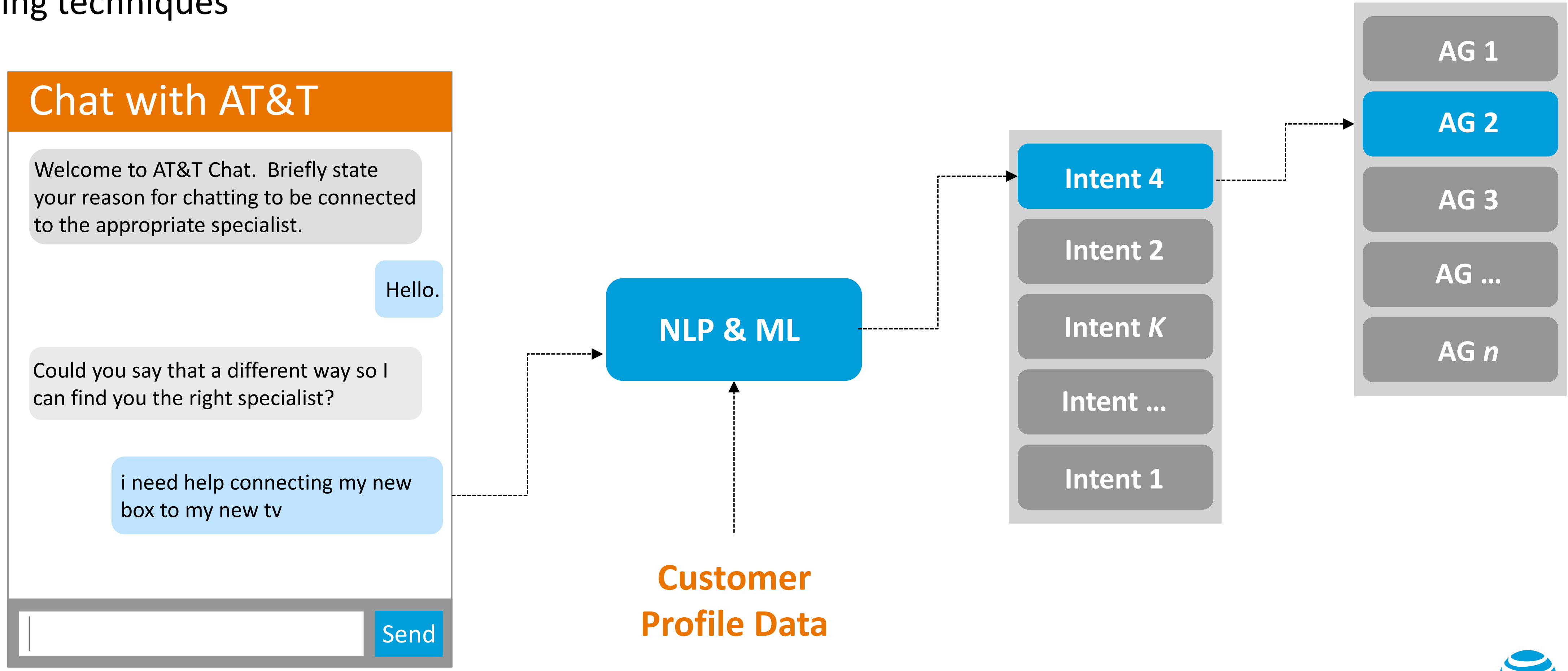


Historic data:
Two agent Groups, non-transfer and one-step transfer

Intent Engine

Our Approach

Use “free text” input to match customer’s intent to the right agent group using machine learning and text mining techniques



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Intent Engine

Our Goals

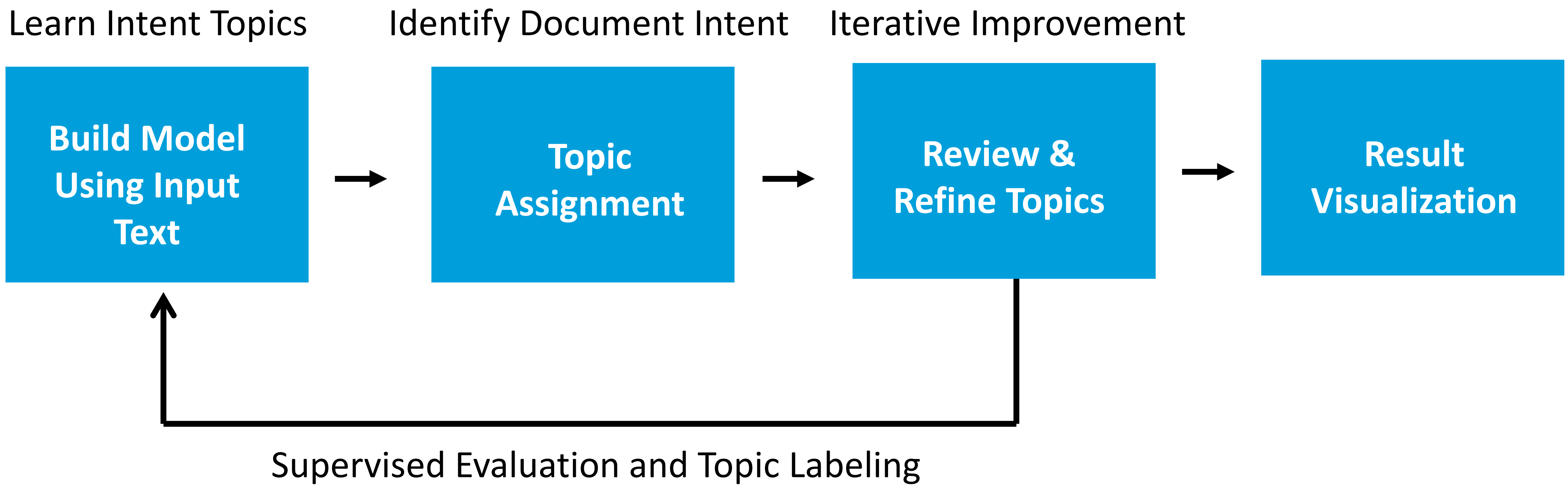
1. Reduce Transfer Rate

2. Reduce Average Handling Time (AHT)

3. Improve Customer Experience

Building An Intent Identifier

Overall Learning and Identification Process



Applications: chat, survey verbatims, call notes

Unsupervised Topic Modeling

"Hi. I am having trouble accessing my email for $SERVICE."
"I can't reset the password for my email."

"Pay my bill. I want to pay my bill"
"Trying to pay my tv/internet bill."

"My internet speeds are slow"
"I am only getting #datarate download speed and #datarate upload."

"How do I go about adding $PREMIUM1/$PREMIUM2?"
"I would like to change the premium channels on my account."

Generation 1: LDA

- Document topic distribution
- Topic word distribution

Constraints:

- Short text reduces observation of word co-occurrence
- Each document is a mixture of topics

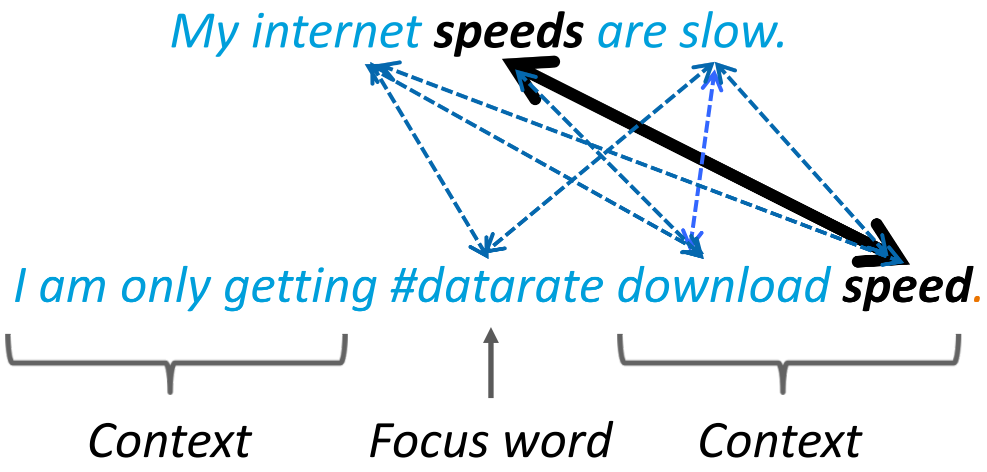
Generation 2: K-Means Clustering + Word Embedding

- Document cluster assignment
- Semantic vector representation for words

Benefits:

- Word expansion captures semantic relationship between words
- Direct map of document to topic

Learning Word Embeddings



Word embedding

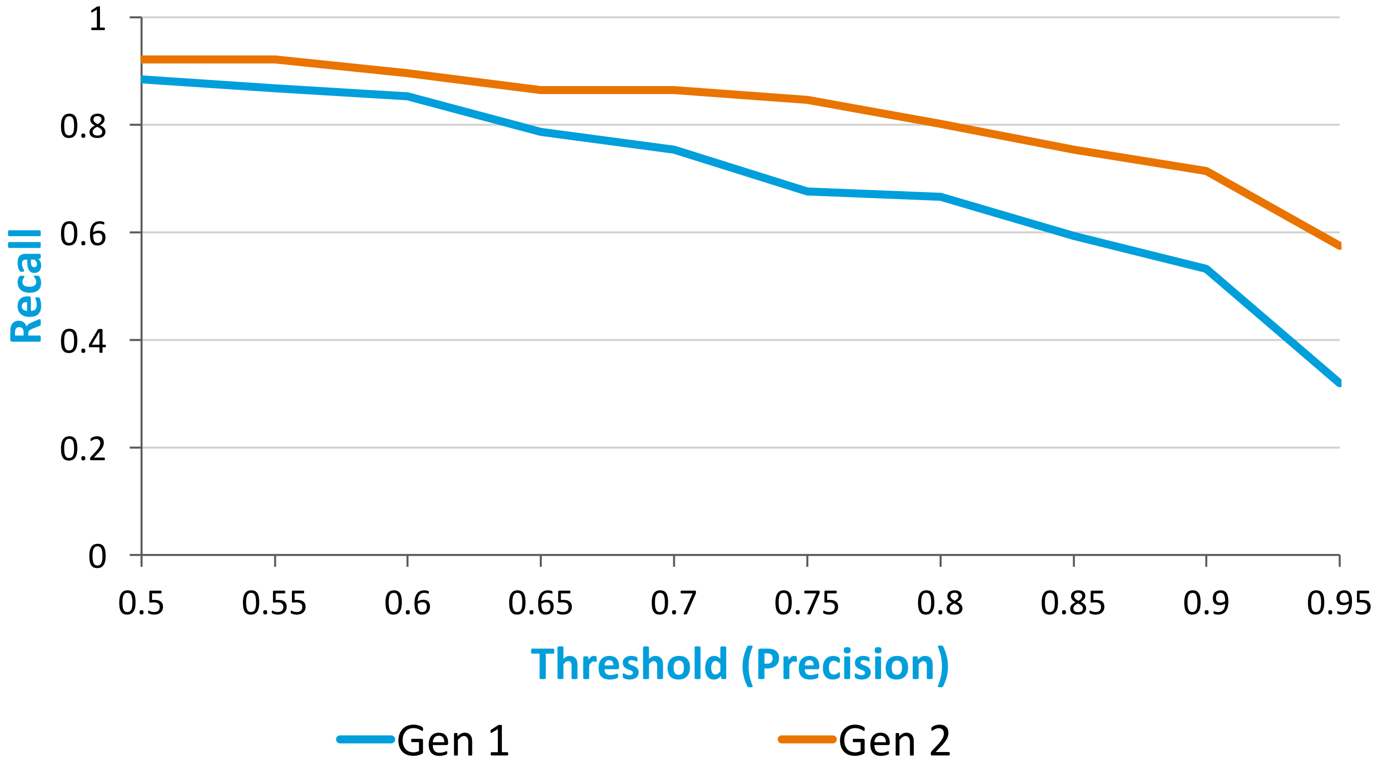
#datarate $[e^1, e^2, \dots, e^d]$
download $[e^1, e^2, \dots, e^d]$
speed $[e^1, e^2, \dots, e^d]$
internet $[e^1, e^2, \dots, e^d]$
slow $[e^1, e^2, \dots, e^d]$

Topic Model Extrinsic Evaluation

Generation 2 Achievements

- Significantly improve topic accuracy
- Improved agent group routing accuracy
- Scalable Spark based implementation
- 16mins for 1M documents with over 17K features

F1 Measure



Data: Sales & Services and Care Non Transfer Chats July 2016

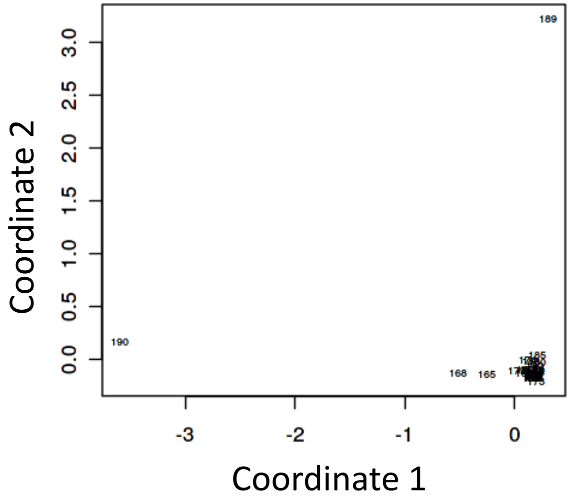
Topic Model Intrinsic Evaluation

Improvement from Word Embeddings over K-means

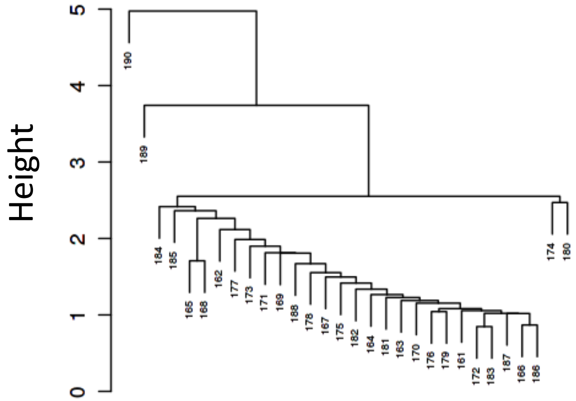
- Lower WCSS (within-cluster sum of distance squares)
- More scattered cluster centroids
- More balanced cluster dendrogram

Before Word Embedding

MDS Plot

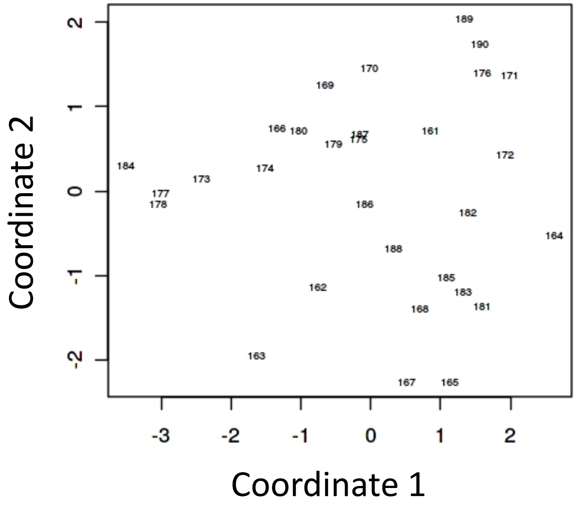


Cluster Dendrogram

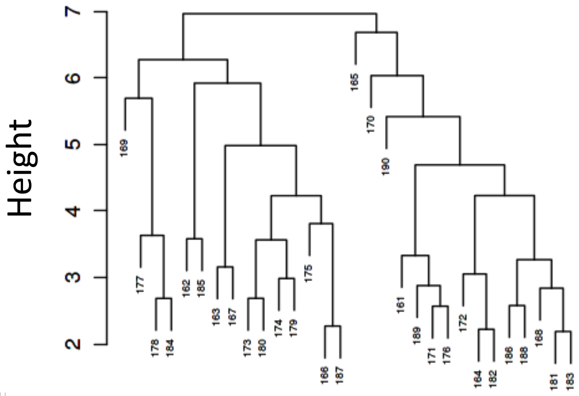


After Word Embedding

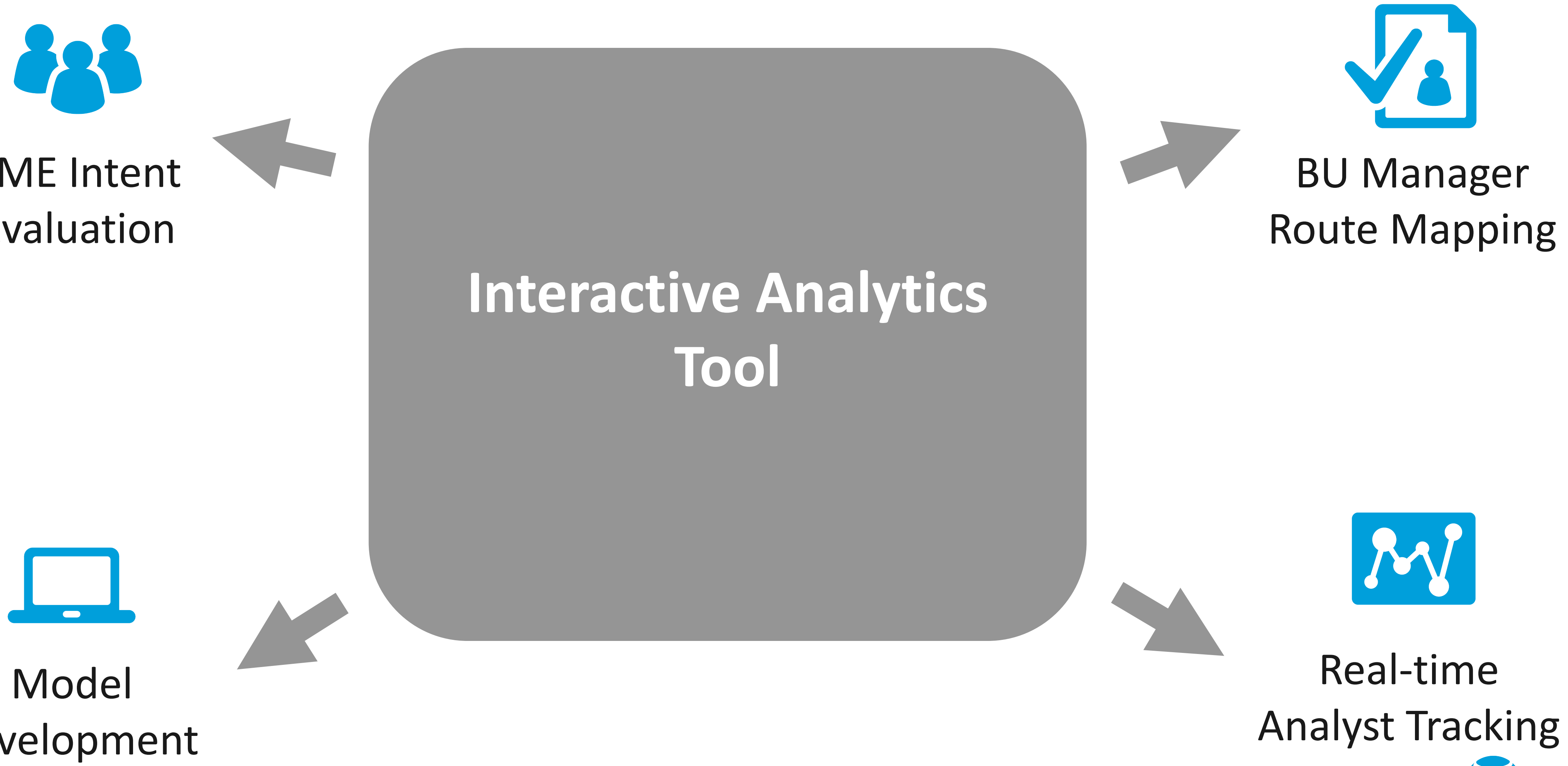
MDS Plot



Cluster Dendrogram



Integration in an Internal Interactive Analytical Platform



Results

Training Data: non-transferred chats, Sales & Services and Care, historic data

Launch pages covered: 4 parent URLs

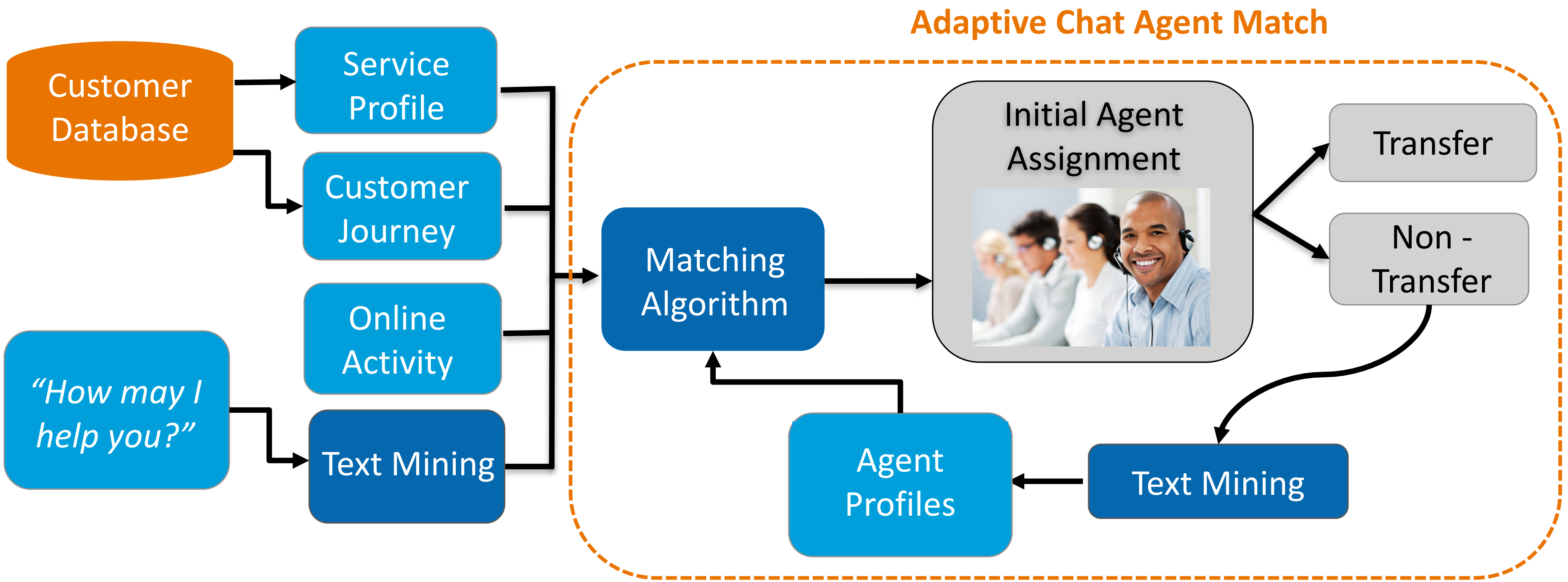
A/B Testing: 80% of traffic to Intent Engine, 20% by BAU

15% Transfer Rate Reduction

13% Reduction in Total Interaction Duration

1/3 Reduction in Drop Out Rate –> Increase in Customer Engagement

Next Step: Adaptive Routing Process



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Key Takeaways

- A Bliss - Orchestra
- Big data and the interactive platform made a big difference
- Power, breakthrough of deep learning, w2v

    Language is organic – evolves along with usage and context

- Topic Model Evaluation still requires supervision -> dream of unsupervised evaluation
- Many other applications in Chat Channel

Teammates

References

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- Spark ML toolkit: https://spark.apache.org/mllib/
- Mallet – Machine Learning for Language Toolkit - http://mallet.cs.umass.edu
- Word embedding skip-gram model:

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- LDA topic modeling:

  Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent dirichlet allocation." *Journal of machine Learning research* 3.Jan (2003): 993-1022.

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