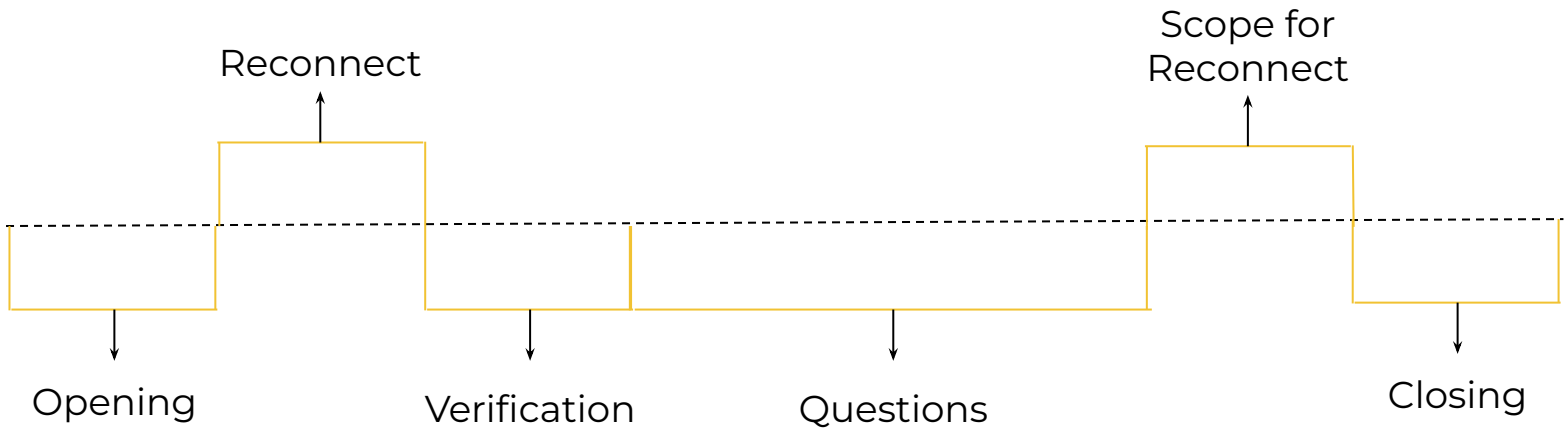
OBSERVE·AI

Call Anatomy

Project Naam-Karan

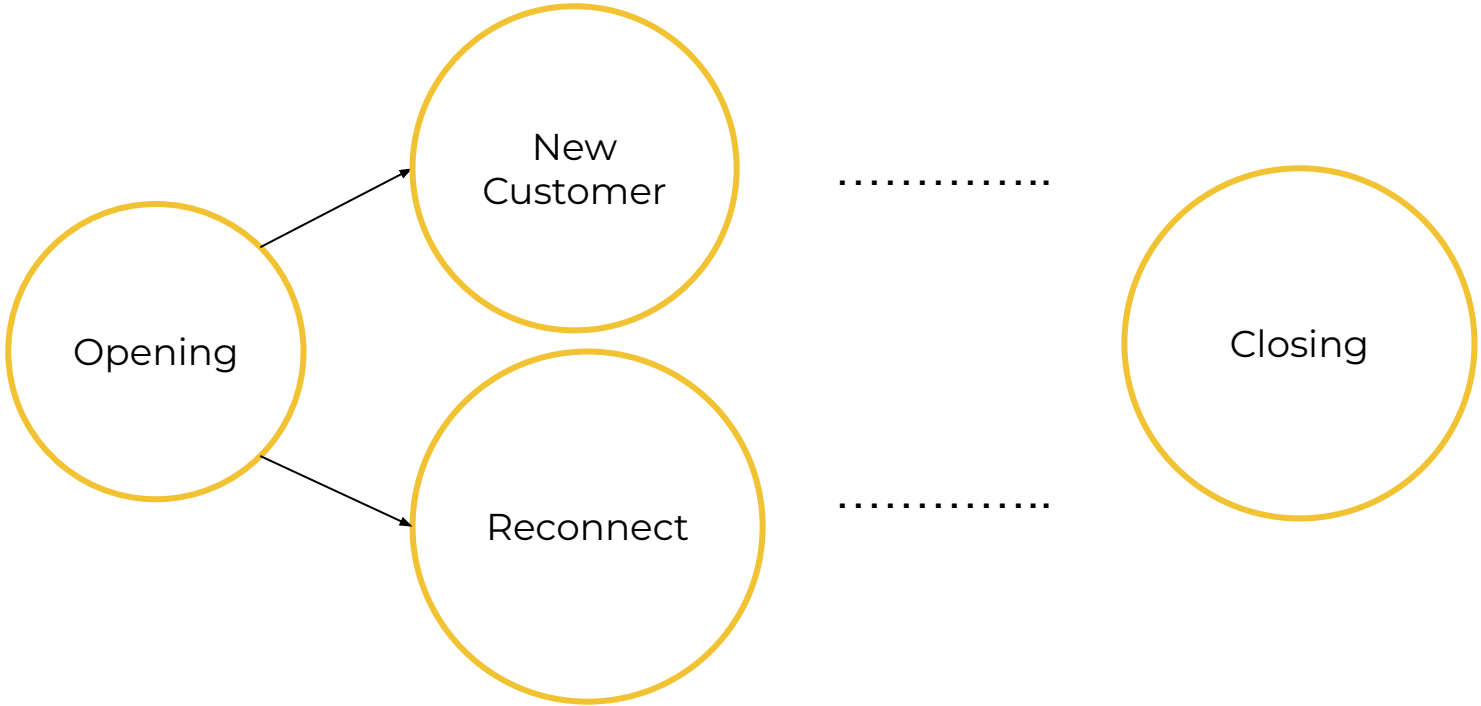
Introduction

Labelling sequences of dialogues with appropriate topics



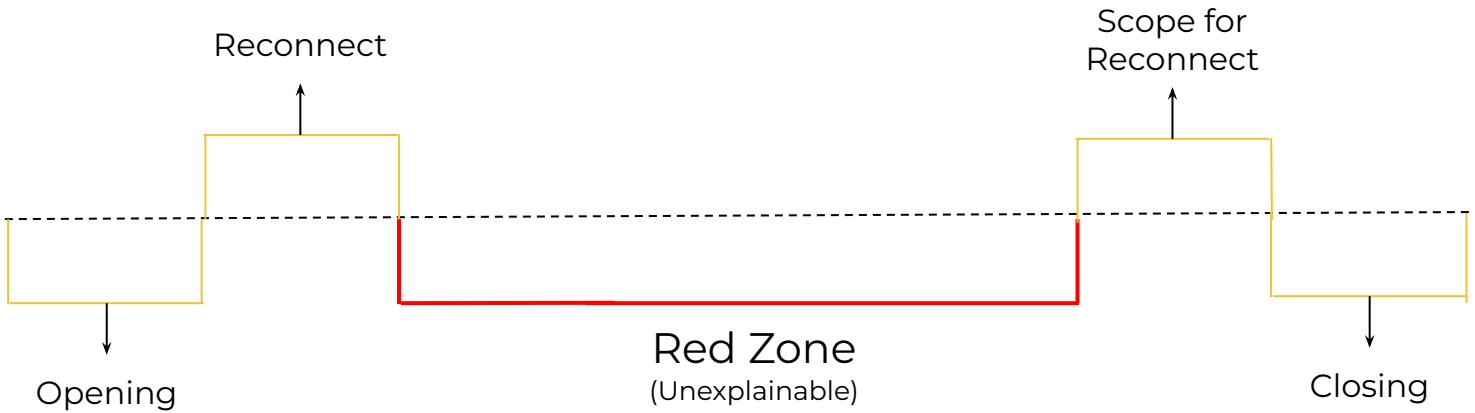
Use Case:

Conversational Map for Script Adherence



Use Case:

Quality Assurance/Customer-Experience Manager Efficiency



Status Quo

Keyword Spotting

- Structure is restricted to Keyword
- Low-Recall System

ML Based Moments

- Broad Topics
- Scalability Issues
- Full Supervision Systems

Custom Requirement

Goal

Increased Understanding of Calls

Least/No Supervision

Highly Scalable

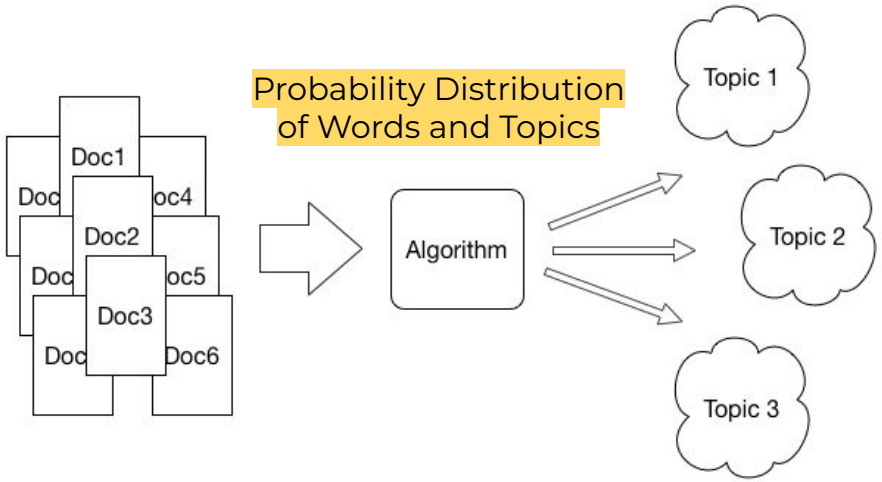
High Performance

Unsupervised Methods

Dataset:

- Refresh Financial (Outbound) - 1101 Calls
- Personal Capital (Not Set) - 1101 Calls

Topic Modelling



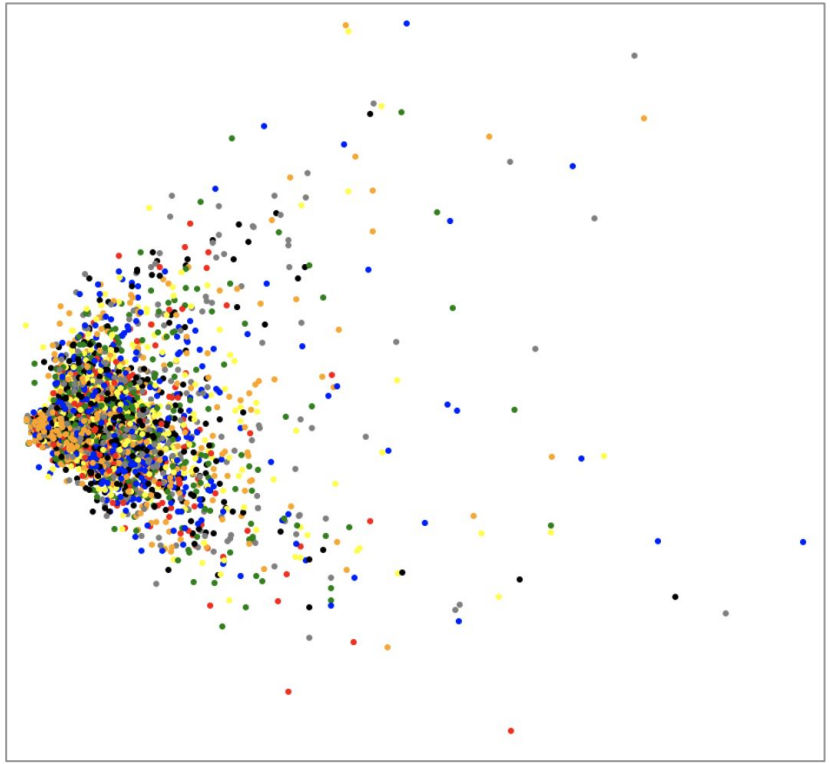
"Opening" and "Closing" can be easily separated

Random topics were inferred

```
(0, '0.026*"right" + 0.026*"program" + 0.018*"email" + 0.016*"credit"')
(1, '0.118*"hello" + 0.059*"refresh" + 0.053*"financial" + 0.037*"calling"')
(2, '0.072*"credit" + 0.027*"program" + 0.024*"right" + 0.021*"payment"')
(3, '0.029*"credit" + 0.022*"payment" + 0.016*"financial" + 0.016*"refresh"')
(4, '0.075*"credit" + 0.027*"right" + 0.019*"score" + 0.016*"build"')
```

Clustering

Dialogue Level (Temporal Colors)



K-Means spreads to the outliers

Points are very near to each other

Dialogue Level

0: [D0, D1, D2, ... D95]
1: [D96]
2: [D97]
3: [D98]
4: [D99]
.....

Aspect Extraction

Inferred Aspects	Representative Words	Gold Aspects
Main Dishes	beef, duck, pork, mahi, filet, veal	Food
Dessert	gelato, banana, caramel, cheesecake, pudding, vanilla	
Drink	bottle, selection, cocktail, beverage, pinot, sangria	
Ingredient	cucumber, scallion, smothered, stewed, chilli, cheddar	
General	cooking, homestyle, traditional, cuisine, authentic, freshness	
Physical Ambience	wall, lighting, ceiling, wood, lounge, floor	Ambience
Adjectives	intimate, comfy, spacious, modern, relaxing, chic	
Staff	waitstaff, server, staff, waitress, bartender, waiter	Staff
Service	unprofessional, response, condescending, aggressive, behavior, rudeness	
Price	charge, paid, bill, reservation, came, dollar	Price
Anecdotes	celebrate, anniversary, wife, fiance, recently, wedding	Anecdotes
Location	park, street, village, avenue, manhattan, brooklyn	Misc.
General	excellent, great, enjoyed, best, wonderful, fantastic	
Other	aged, reward, white, maison, mediocrity, principle	

No mutually exclusive aspect found

No Structure (Topics are not well defined)

Context defines the topics not anchors

*https://www.comp.nus.edu.sg/~leews/publications/acl17.pdf

Why Unsupervised Methods failed:

No

Domain Specific knowledge fed

No

Fixed number of topics defined

No

Pre-Defined Knowledge on Topics

Customer Requirement

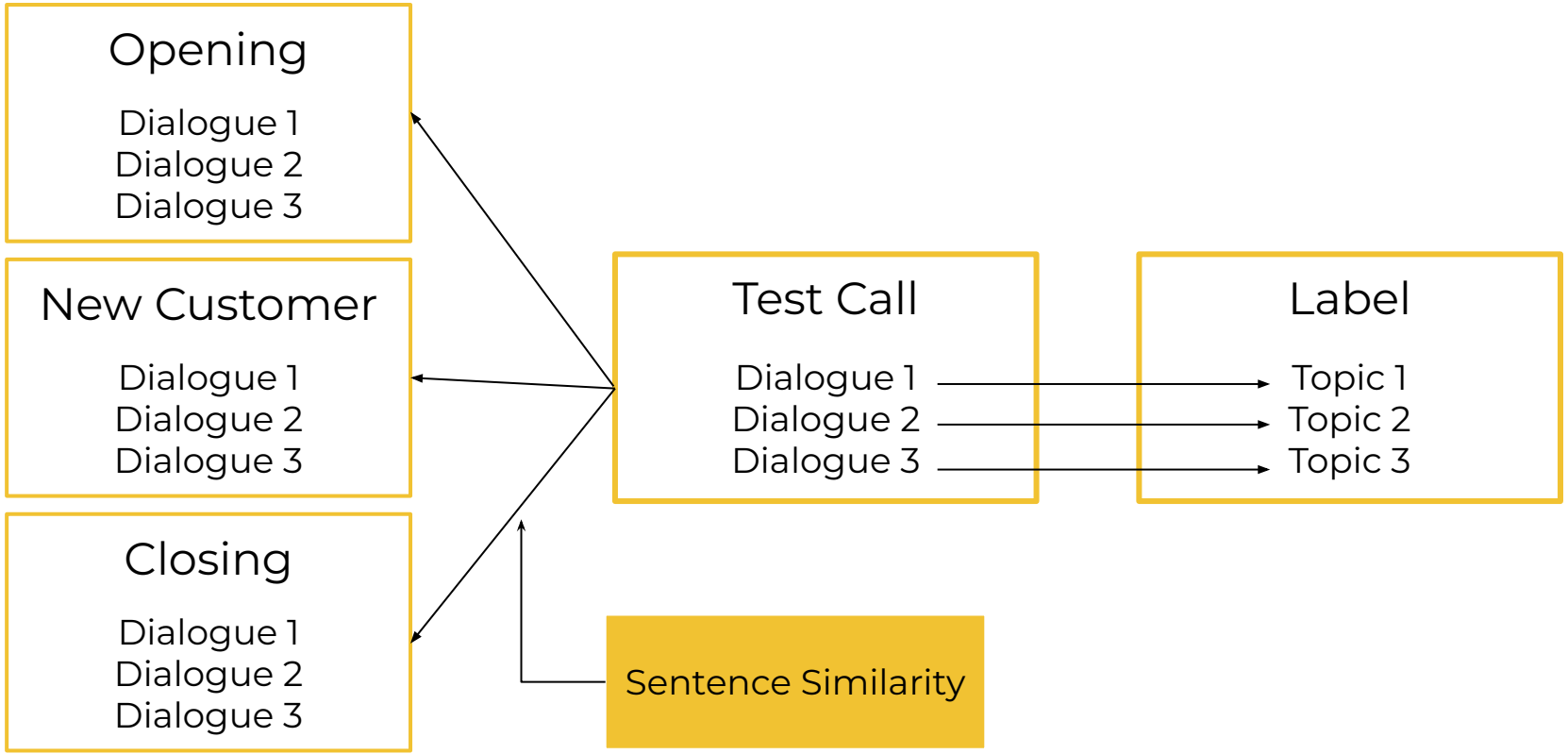
Not Fulfilled

Structural Study

Dataset:

- Personal Capital (Not Set) - 500 Calls

Existence of Generic Topics



Existence of Generic Topics

‘Opening’ and ‘Closing’ had 100% Precision and Recall

85% accuracy on Top-2

76% accuracy on Top-1

Most confusion between pair of classes

But…

Requires fully supervised/labelled data

Not Scalable for each customer

Temporal Analysis

Figure 1: Continous Splits

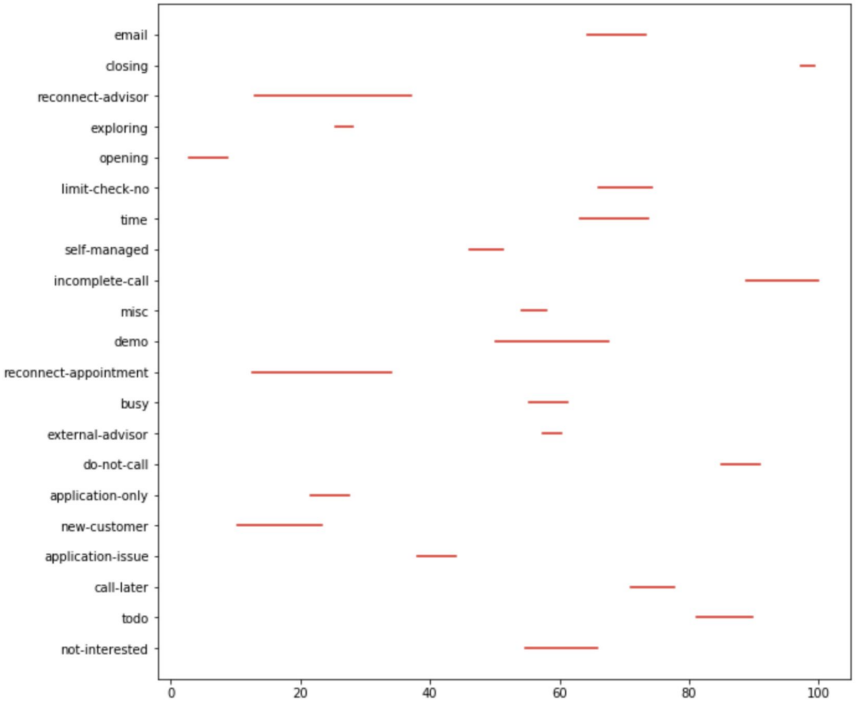
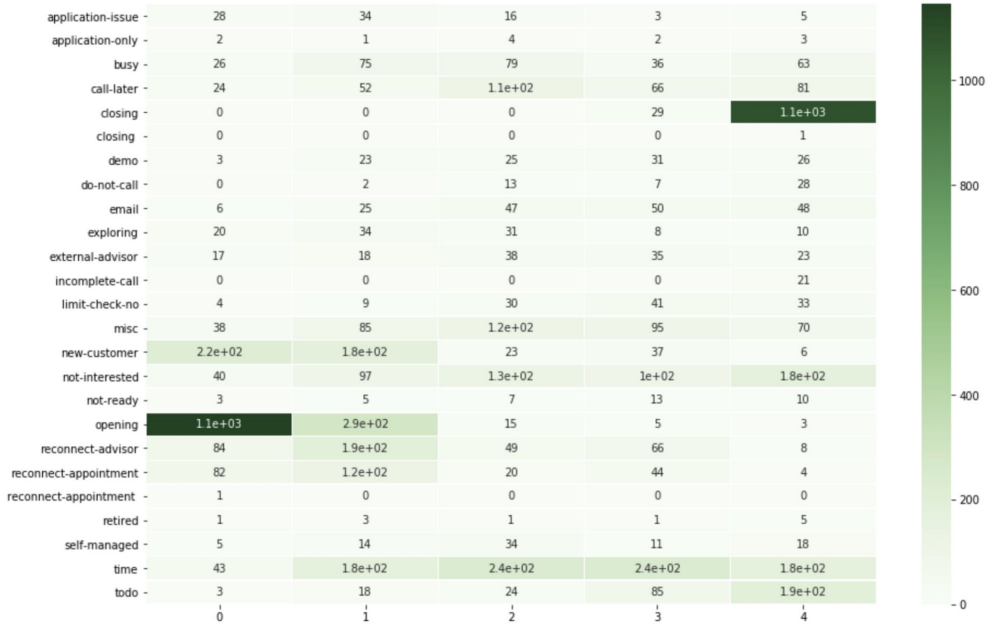


Figure 2: Discrete Splits



Takeaways

Capture Larger Context

(Not rely on keywords)

Exploit Temporal Features for Conversational Map

Supervision works well but is not scalable

Try Semi-Supervised Methods

Semi-Supervised Method

Dataset:

- Refresh Financial (Outbound)
  - Train - 1 Call
  - Test - 5 Calls

Hypothesis: Tag dialogues with topics based on training seed

Insights:

‘Opening’ was detected every time

‘Closing’ and ‘Verify’ got correct in 3 out of 5

‘Upsell’, ‘Help’, ‘Credit Card’ got confused

Action Items:

Greater Context required for confusing classes

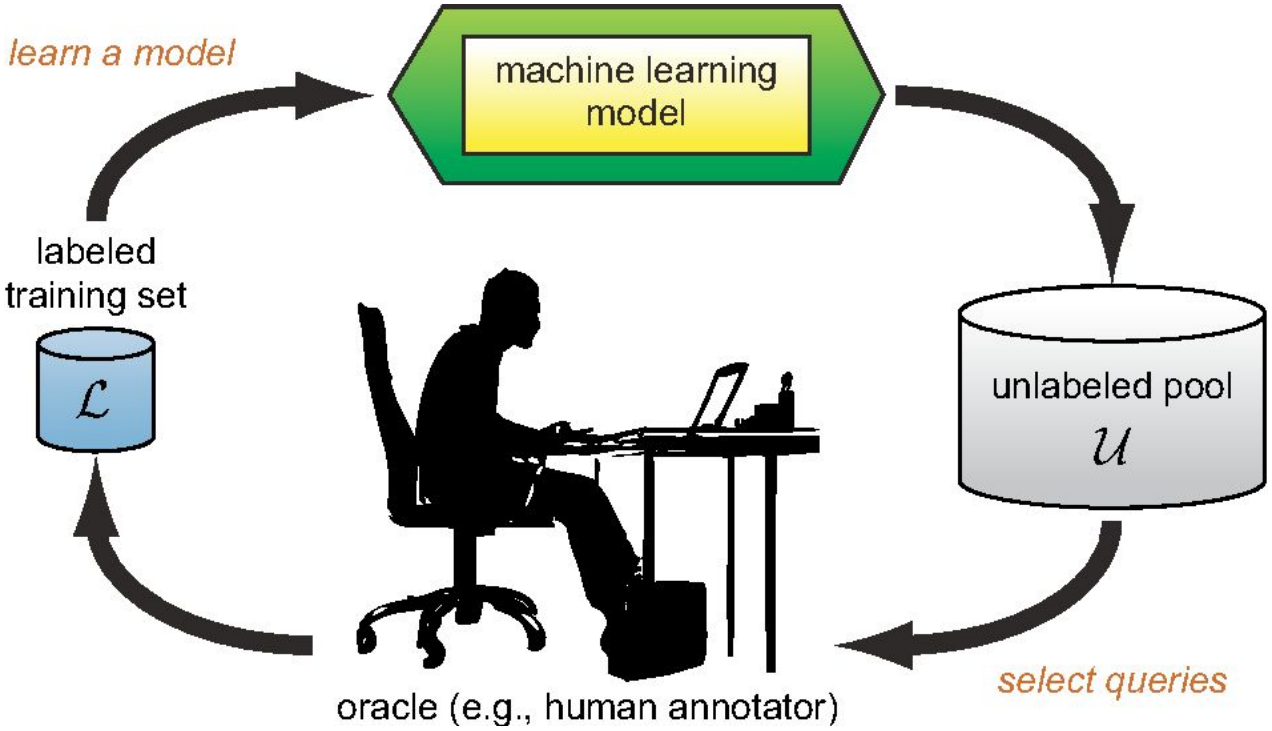
Active Learning can be approached

Our Approach

Dataset:

- Personal Capital (Not Set) - 500 Calls

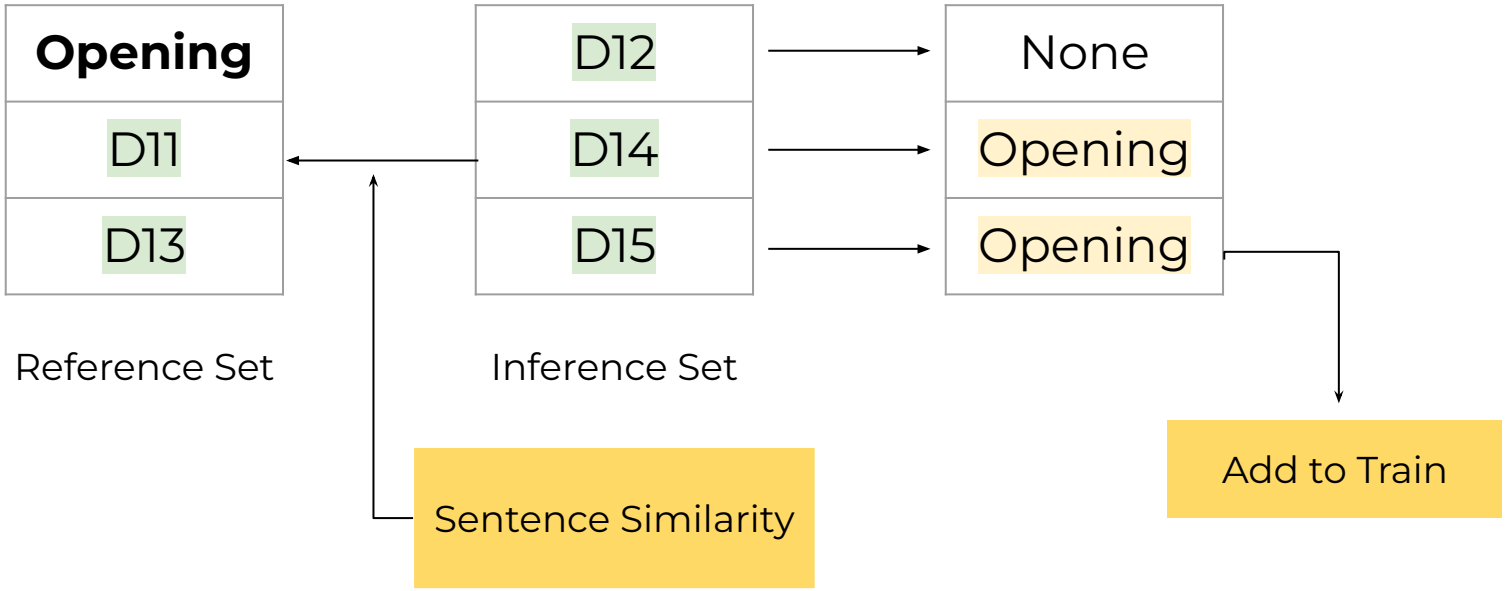
Active Learning

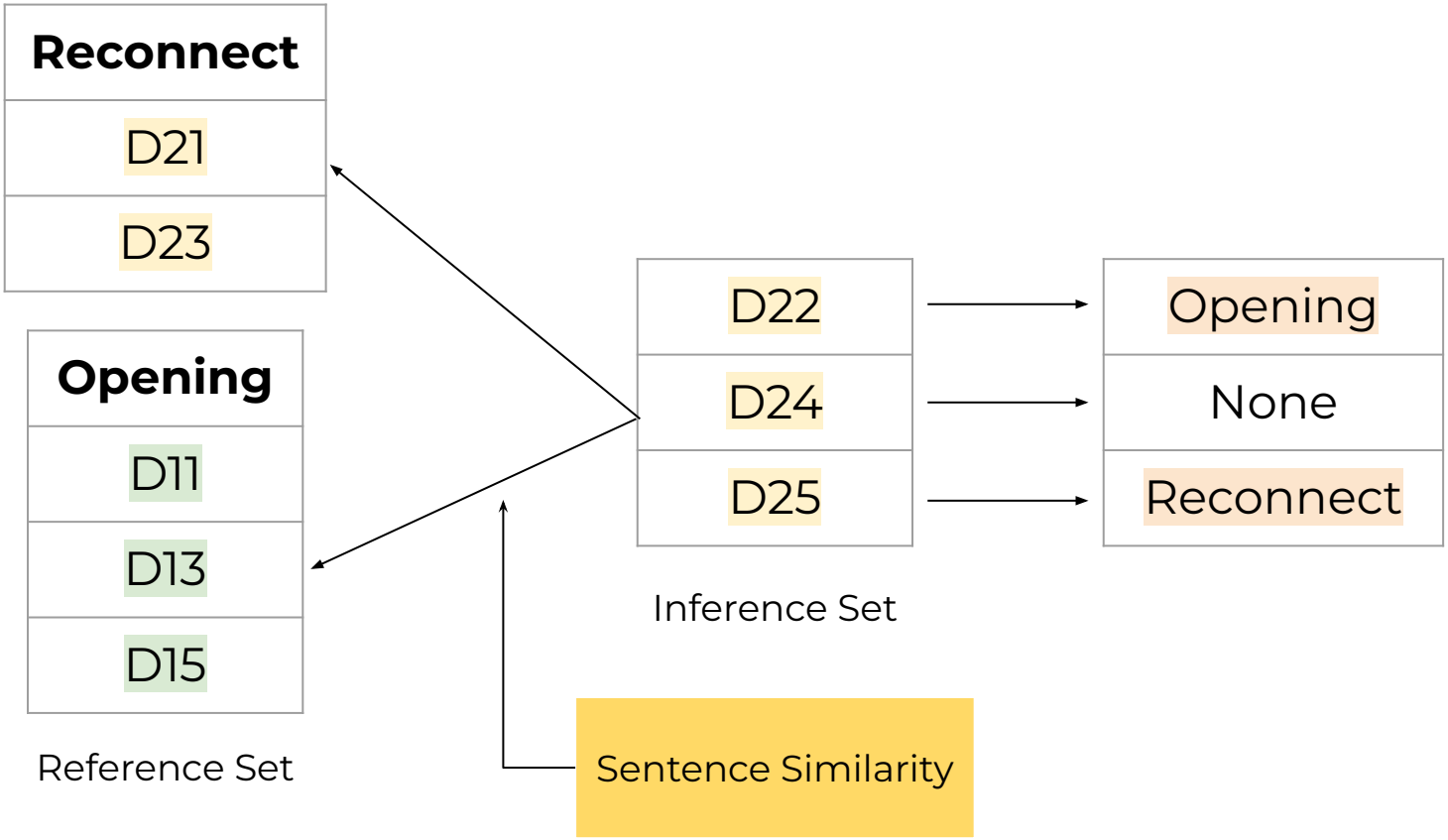


Division of Temporal Segments

Call 1	D11	D21	D31	D41	D51
Call 2	D12	D22	D32	D42	D52
Call 3	D13	D23	D33	D43	D53
Call 4	D14	D24	D34	D44	D54
Call 5	D15	D25	D35	D45	D55

Iteratively add classes by seeing segments one by one


Opening
D11
D13
D12
D14
D15
None
Opening
Opening
Reference Set
Inference Set
Sentence Similarity
Add to Train


Reconnect
D21
D23
Opening
D11
D13
D15
Reference Set
D22
D24
D25
Inference Set
Opening
None
Reconnect
Sentence Similarity

Tool: http://34.73.58.232:8888/

Result

High confidence valid predictions observed

Scalable

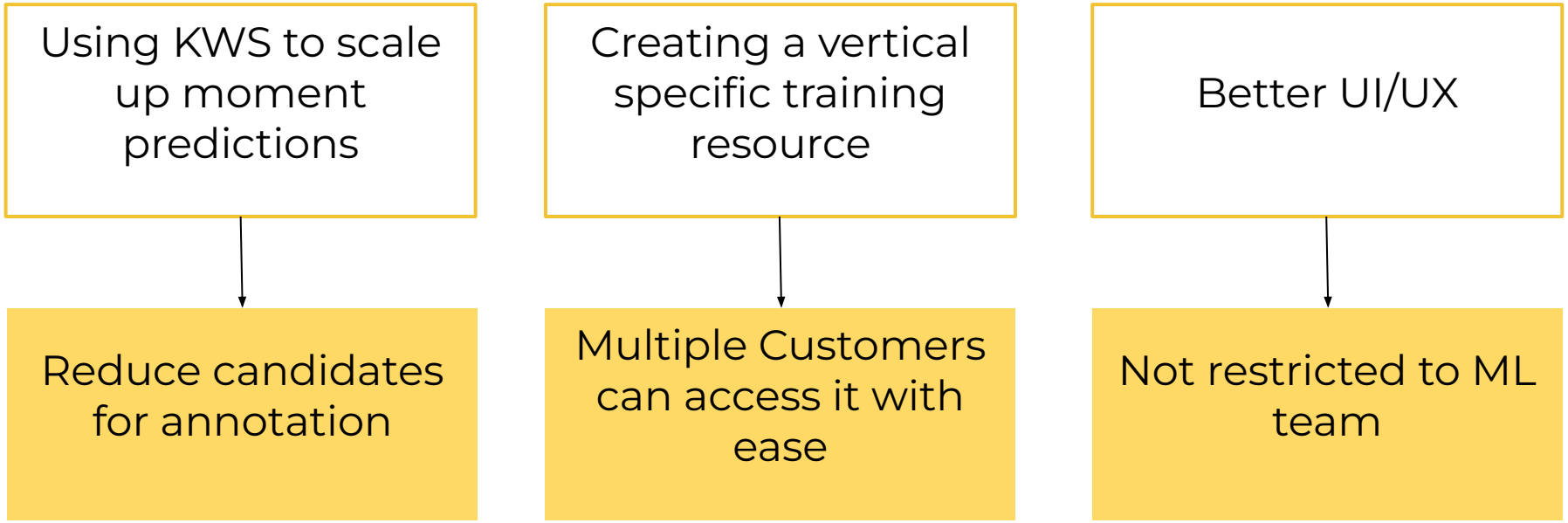
Low API Latency

(Time and Resource)

Best Part

Minimum Human Effort
Minimum Supervision

Future Work


Using KWS to scale up moment predictions
Creating a vertical specific training resource
Better UI/UX
Reduce candidates for annotation
Multiple Customers can access it with ease
Not restricted to ML team

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Thank You