LPar - A Distributed Multi Agent Platform for Building Polyglot, Omni Channel and Industrial Grade Natural Language Interfaces

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June 29, 2020

ABSTRACT

The goal of serving and delighting customers in a personal and near human like manner is very high on automation agendas of most Enterprises. Last few years, have seen huge progress in Natural Language Processing domain which has led to deployments of conversational agents in many enterprises. Most of the current industrial deployments tend to use Monolithic Single Agent designs that model the entire knowledge and skill of the Domain. While this approach is one of the fastest to market, the monolithic design makes it very hard to scale beyond a point. There are also challenges in seamlessly leveraging many tools offered by sub fields of Natural Language Processing and Information Retrieval in a single solution. The sub fields that can be leveraged to provide relevant information are, Question and Answer system, Abstractive Summarization, Semantic Search, Knowledge Graph etc. Current deployments also tend to be very dependent on the underlying Conversational AI platform (open source or commercial), which is a challenge as this is a fast evolving space and no one platform can be considered future proof even in medium term of 3-4 years. Lately, there is also work done to build multi agent solutions that tend to leverage a concept of master agent. While this has shown promise, this approach still makes the master agent in itself difficult to scale. To address these challenges, we introduce LPar, a distributed multi agent platform for large scale industrial deployment of polyglot, diverse and inter-operable agents. The asynchronous design of LPar supports dynamically expandable domain. We also introduce multiple strategies available in the LPar system to elect the most suitable agent to service a customer query.

1 Introduction

Natural Language Queries from customers of any large Enterprise are very diverse and complex. A lot of effort to model and automate these in last few years have been as monolithic applications leveraging Conversational AI tools available in market or available Open source.

While these efforts have given encouraging results but have also highlighted numerous challenges.

Following are some of the key challenges -

- NLP is a constantly evolving space and months of development work done to build and deploy these Agents very quickly become out of date as new Research or tools come into market.
- Monolithic nature of design of these Agents makes the development slow and very difficult to federate, leading into increased time to model the depth and breadth of relevant domain of the enterprise.
- Addition of New Skills to the Agent, along with build effort, also requires extensive regression testing effort as training data of new skill can very easily impact already existing skills.
• Queries that require automation vary vastly in terms of number of turns and data points/slots required from user to provide a resolution with optimal experience. Some factoid based queries can be resolved in a single pass while other goal oriented skills require complex multi turn conversation. Also there are some queries tend to be more suitable to a search domain. Efficient coverage of the depth and breadth of the domain requires more that just one tool to model the queries.

• The interpretation of user queries tend to be very literal basis what a user said/texted. To have a meaningful communication, it is very important to interpret what user said basis deep understanding of the user and his/her current context.

With LPar, we intend to resolve many of above challenges and provide a framework that provides stability and consistency to large Organizations.

1.1 Tools for building Conversational Systems

As mentioned above, Customer queries are very diverse and it's always a challenge and no one tool can be used to model them all. Based on our experience and research we following tools currently available

**Goal Oriented Agents**  Goal Oriented Bots use Natural Language Understanding, dialog management and response generation to fulfill goal(s) for the user of the system. These tend to gather user inputs (Slots) in multi turn conversations and retain context across turns. Once a user's intent and inputs have been confirmed, these perform a fulfilment function leveraging APIs. Last few years have seen increased adoption of these in the industry and are used to automate standard user interactions like checking flight status, flight bookings, checking balances etc. With the current commercial and open sources tools in market, these require conversation modelling and build.

**FAQ Agents**  FAQ bots generate contextual vectors for large number of question and answer pairs and indexes them in a persistence store. They usually serve user queries in a single pass. The user queries at the run time are transformed into corresponding contextual vector and a Nearest Neighbour search is performed on the persistent store using various distance measures like cosine similarity, Euclidean Distance, Manhattan Distance etc. These are a great tool to cover a large breadth of queries with in the domain very quickly but usually lack the multi turn conversations and hence are not suitable for interactive queries. They also require a content curation, review and management effort from the SMEs to identify and maintain relevant Question and Answer pairs.

**Question and Answer Agents**  Question And Answer systems intend to provide a concise response to a natural language query from the user over a large knowledge Base. This task requires natural language understanding of user query, Knowledge representation and reasoning over a domain. A question and answer system apart from providing the most relevant document, also looks to provide the span of the answer with in the document.

**Semantic Search Agents**  Semantic Search systems look to leverage the advances in Natural Language Processing to make search queries more relevant. Multiple tasks in NLP domain like embeddings, Entity Extraction, Sentiment Analysis, Named Entity Recognition are performed on content during the time of indexing to make the content more easily search-able during the query time. Context Vectors are created for user queries and nearest neighbour search is performed during the query time to find most relevant matches. Semantic search is usually a good fallback option for conversational system as they increases the domain coverage of the system without requiring development effort for every topic. It can also be a handy tool to reduce the expensive human hand over costs as some of the answers can be provided to the user by search itself.

**Knowledge Graphs**  Knowledge Graphs are a powerful tool to represent interconnections of the world. They are used to store entities, relationships and attributes. They have been extensively utilised to model the knowledge of the domain and make the information more easily search-able through its interconnections. They have been used to build internet scale search systems and virtual agents.

2 Design Goals

Based on the review of above available tools and the challenges faced in current implementations, following are the key design goals for LPar

**Multiple Application Support**  LPar envisions to provide support for multiple use cases from a single deployment. This will allow enterprises to scale the solution very quickly.
Omni Channel Lpar supports most prevalent channels of communication that are required by modern enterprises. These include Digital (web and mobile), Social Media, email, SMS and IVR.

Moving from Monolith Centralised Agents to Distributed Micro Agents One of the key design goals for LPar is to have distributed Micro Agents that specialise in one task or topic. This allows Conversational systems to be more agile, flexible and maintainable. The design principles of leveraging micro components have already proven within the wider software industry.

Support for Multiple Tools (Conversational AI, Question and Answer Systems, FAQ Automation, Semantic Search, Human Agents) As described in the introduction section, there are multiple tools available for modeling natural language queries of users of a Conversational System. We were keen to enable designer and developers of conversational systems to use the most suitable tool to model user queries. The framework intends to provide seamless switching across tools.

Polyglot and Technology Agnostic There are numerous Open Source and Commercial tools available in the market for building conversational systems. With a fast moving technology domain, the shelf life of any of these systems is very hard to predict. The framework intends to provide an adapter based design pattern to maintain loose and temporal coupling with these tools. This will enable enterprises to very quickly wholly or partially migrate to newer, more robust tools as they come.

Dynamically Expandable Domain Like any machine learning system, agility and frequent updates is important to any conversational system. LPar aims to provide capability to add/update skills without bringing down the overall system.

Policy driven Disambiguation In a multi agent setup, there will be scenarios where more than one serving bot may be able to answer a query. It is important to have a policy driven approach to Disambiguation. Currently LPar supports 3 different policies. We expect the Policies to continue to evolve in future.

Utilize Internal and External Context A user of a conversational system has a context from historical sessions and current session. To make conversations more natural, systems need to effectively utilise this information to have a more engaging conversation with the user. The context can also be leveraged to predict the next best action for the user. Most large enterprises capture a customer’s various interactions across their application landscape. As users engage with applications, they generate interaction data which can be effectively harnessed by conversational systems to improve the experience of the users. LPar is envisioned to get External context from these systems of interactions and leverage the same to improve customer experiences.

Experimentation in production and Offline Natural language processing is a fast evolving space. We were keen to provide native support in the framework for fast experiments with minimal impact on users of the system.

Adaptive Dialog Management through Hyper Personalization To deliver optimal user experience, LPar endeavours to understand its user’s context by integrating with Enterprise Context Service and personalise user’s journey.
3 LPar - System Architecture

Below is the high level diagram representing various components of LPar.

3.1 App Store

LPar platform is designed to support multiple Natural Language Apps from a single deployment. App store retains metadata about for all Natural Language applications supported by the system. These applications ideally would support different domains across the enterprise.

- Name of Application
- Application Identifier
- Identifiers of Channels Supported
- Serving Matrix
- Resilience Rating for the application
- Data Classification Rating of Conversational Application
3.2 LPar App Router
The LPar App router routers the requests to appropriate Natural Language Apps with in the system basis the Application Identifier that is generated by the App store.

3.3 Natural Language Apps
Natural Language Apps are logically separate applications that support a business function. A single Natural Language app can comprise of multiple Agents and PODs.

The Organization design of the Natural Language App is crucial to overall quality of the service the app can deliver. The platform supports for both Hierarchical and Flat Organisational structures basis the requirement of a domain. For some enterprises, there may be a merit for the Natural Language App Organization Design to resemble closely to the structure of their respective areas. This can allow for Federation and parallelisation of the Natural Language App build and support to the most relevant teams rather than in a central structure.

3.3.1 Customer Service Agent
Customer Service Agent is responsible for overall experience of the user. This component performs following functions:

- Act as Front line agent that receives user’s request, understands user’s context and recommends the most suitable Agent with in the system to service the request
- Executes the Agent Selection Process leveraging Broadcast Only and Search and Multicast strategies available in the LPar system
- Responsible for establishing user session and to maintain context of the user as the conversation progresses
- Leverage the Global User Context Service to personalise customer journey. Also, update the local context into the Global User Context Service.
- Perform specialised routing as defined in the routing profile

The key point to note is that the main function of the Customer Service Agent is to try and innately understand the user of the system. It is not a master agent that will have the knowledge of the entire domain.
3.3.2 Key Data Stores

Natural Language Apps utilizes a number of data stores to service user queries. The data stores are separate for all every Natural language App on the platform to support data privacy and segregation requirements.

Following is the brief description of each of the data store

Session Store

It maintains the user session and context as conversations progress. Customer Service Agent component utilizes and maintains this store to create and update user sessions. Every user session has an Serving Agent field that specifies the Agent with which the conversation is currently progressing. Customer Service Agent forwards all user queries to Serving Agent’s private address and processes its response. When the Serving Agent is not able to service a user's query and replies with an out of scope response, agent selection process is triggered as described in later sections. Session store also maintains Context which is Intents and Entities as provided by Serving Agents in their responses. In one Session a customer can be serviced by multiple serving agents basis the query from the user.

Serving Store

It stores the list of available Pods and Agents which are available with in the system and can be directly reached by the Customer Service Agent. Following are they key attributes that are maintained by Serving Store

- Agent Identifier
- Agent Name
- Agent Version
- Agent Type (POD or Agent)
- Centroid of vectors of utterances used to train the agents
- Connection protocol
- Private Address (Adapter Request and Response topics)
- Status (Online or Offline)
- Scope (Internal or External)
- Class (Conversational Bot, FAQ bot, Q and A system, Semantic Search, Knowledge Graph, NA)
- Agent Rating (Beginner, Intermediate, Professional, Expert)
- Channels Supported
- Average Response time

User Store

It maintains the User profiles for the system. LPar system can also work with external user profile stores like CRM systems. User Profiles store users identifies across different channels so than an Omni Channel experience can be provided to the user. They can start a conversation in one channel and continue the same in a different channel. The attributes from User Profile store are key for the Customer Service Agent to provide a personalized experience to user. Attributes from User Profile are leveraged to choose the Customer Service Agent Persona that is most suitable for the customer.

Feedback Store

It logs the feedback that users provide through various surveys that are run by the system. This the feedback and other parameters are utilized by the system is to update the Agent Rating. Agent Rating is leveraged by the system in Response Selection Policies. These become relevant when Multiple Agents provide responses to a users query

QueryCache

All incoming user queries in the system are logged in the query cache by the Customer Service Agent. It also records the response provided by the Agent. When Agent Selection Process is executed, QueryCache is leveraged to log responses from multiple agents and finally most suitable response is selected.

Routing

Routing store is used by the system to store any recommended routing options for the user basis the users interactions and transactions across the enterprise.
3.3.3 Anatomy of a POD

Pod is a core construct of Lpar that brings together a capability around a high level topic for the Domain of the Application. A POD can comprise of multiple Agents or PODs as well giving scalability to expand the domain of Natural Language application in both depth and breadth. Agents and PODs can be dynamically added or removed at the run time without any impact to overall Application. A Pod can have Agents of same or multiple different Classes (Conversational Bot, FAQ bot, Q and A system, Semantic Search, Knowledge Graph). A suggested way to model a domain would be to have a healthy mix of Agents belonging to different Agent Classes basis the requirements of the domain.

The Pod Co-ordinator is responsible to find the most suitable Agent and provide its response for a particular user query leveraging all the members of the POD listed in the Pod member store.

![Structure of a POD](image)

Pod Addresses

- Pods subscribe to Broadcast Request topic and publish processed response back to Broadcast Response topic
- Pods can dynamically subscribe and publish back to multicast topics during the run time
- Pods also have individual request and response topics through which they can be contacted once a sessions has been established with them

Following are the examples of Agents that belong the Payments Pod

- Bill Payments Agent (Goal Oriented Agent)
- Direct Debit Agent (Goal Oriented Agent)
- Payment Status Agent (Goal Oriented Agent)
- International Payments Agent (Goal Oriented Agent)
- Payments FAQ Agent (FAQ Agent)
- Payment Terms and Condition Agent (Semantic Search Agent)

3.3.4 Anatomy of an Agent

An Agent is the atomic unit of the Natural Language App bringing in a focused execution or query capability to the Application. A typical agent will perform Natural Language understanding to understand the user’s intent, extract entities from user’s input, perform validations, manage the dialog, execute an action and provide a response back to the user.

Every agent integrates with an Adapter to keep the over all Application vendor agnostic. LPar system supports development of Agents using any commercial or open source solution. Multiple agents built on different technologies can co-exist with in a single Natural Language Application.
Agent Addresses  Agents have three key addresses using which they can be passed a message for a response.

- Agents subscribe to Broadcast Request topic and publish processed response back to Broadcast Response topic
- Agents can dynamically subscribe and publish back to multicast topics during the run time
- Agents also have individual request and response topics through which they can be contacted once a sessions has been established with them

3.3.5  Agent Selection Process

Customer Service Agent (at Application level) and Pod-Coordinator (at Pod level) are the two components that have the responsibility to run the Agent Selection Process. There are two strategies for Agent selection namely **Broadcast only** and **Search and Broadcast**. The Natural Language App developers are expected to identify the most suitable strategy during the build time and configure the same in the App store settings.
Following flowchart depicts the agent selection process

Once the Agent selection process is complete and an agent has been identified, the user session is bound to the selected agent. Subsequent queries are sent directly to the Agent. If the agent is able to fulfill the query then the dialog continues with the Agent. If at some point the agent is not able to provide response to the user query and provides an out of scope response, this leads to the Agent selection process getting called again to identify the next agent.

Response Selection Policy

3.4 Live Chat and Human Agent

Most Enterprise platform require capability to hand over to human agent under multiple different scenarios. Following are the standard key scenarios that require Human Agent Hand Over and are supported by LPar System

- User Explicitly asking to talk to a human
- A customer’s sentiment drops below a threshold
• Multiple Out OF Scope responses from the Agents with in the system
LPar system provide connectors to multiple popular Live Chat platforms.

### 3.5 Utility Services

LPar system provides multiple utility services to the App developers to support the App development effort. These are typically reusable services that are required by multiple applications.

Following is the brief about each of the service:

- **PII Redaction** - The service uses regular expression and machine learning algorithms to redact PII information.
- **Profanity Filter** - Identify if users are using inappropriate language and redact the same.
- **Sentiment Analysis** - Provide the Sentiment of user queries.
- **Notification Service** - Provides capability to send Push Notification to the users to enhance the experience.
- **Personalisation or Context Service** - Provides Real time Context information for the user from across the enterprise that is leveraged by the platform to simplify customer experience.
- **GraphQL APIs** - These profile a unified schema for the Agents to utilize to support the integration with rest of the enterprise.
- **Validation APIs** - Validation APIs provide a common framework of validation across the Agents.

### 3.6 Channel Adapter

Channel Adapters provide multiple connectivity options for the platform to integrate with Digital, Social Media and Voice channels. They abstract the channel connectivity details from rest of the platform.

### 4 Experimental Setup

Retail Banking domain was chosen for creating an experimental setup. Following are the multiple agents that were created in the system:

- Balance and Transaction Agent was created to have the responsibility to show customer balance for multiple accounts.
- Product Finder Agent was created to provide answers for Product related Queries.
- Branch and ATM Finder Agent was created to provide responses about Branch and ATM locations.
- Payments Agent was created to showcase payment execution capability.
- Connect Agent was created to provide the human handover capability.

Multi channel capability was added to the system with Adapters for Facebook Messenger, WhatsApp and Amazon Connect (For Voice).

Along with core intents to support the goal that each Agent was designed for, we also created an IdentifyYourself Intent in all Agents. On invocation of this intent with user utterances like “who are you” the Agent responded with its name.

We fired multiple different utterances in no specific order to try the capability of the system to seamlessly assign most relevant Agent to user session and provide quick responses to the customer. We also tried utilizing data that was provided by user to one Agent into another agent to verify the context retention capability of the system. We could demonstrate through our experimental setup LPar system is able to assign most relevant agent to support different user queries. The response times were also within the acceptable limits.
Hello! I am Barclays Assistant.

Hello, how can I help you?

Barclays supports business products like Community Account, e-Payments Plan, Mixed Payments Plan, Barclays Business Tariff, Business Free Money Transmission Quarterly. Please enter product name.

What are the products Barclays is offering?

I am your friendly ProductFinder lex bot.

Who are you?

Where is my nearest Branch?

Please stay tuned as I do some clever thinking to answer your question.

May I know postcode of your nearby location?

The address of your nearest branch is - Building No.18/22, Liverpool Road, Liverpool.

Who are you?

I am your friendly BranchAndATMFinder lex bot.

Type a message

What is my balance?

Please stay tuned as I do some clever thinking to answer your question.

May I know your account type please?

What is your account number?

Are you sure you want to see the account balance for account type Saving and account number 10008?

Your balance is: 5000

I am your friendly BalanceAndTransaction lex bot.

I want to make a payment.

Please stay tuned as I do some clever thinking to answer your question.

Please enter the recipient's account number to whom you would like to make a payment.
I am your friendly BalanceAndTransaction lex bot

I want to make a payment

Please stay tuned as I do some clever thinking to answer your question

Please enter the recipient's account number to whom you would like to make a payment

700056

500

Are you sure you want to pay the amount 500 from your account number 10008 to account 700056? Please confirm

yes

Payment done successful of Amount 500 from account number 10008 to account 700056

I am your Payments bot.

please stay tuned as i do some clever thinking to answer your question

we are handing you over to an agent who will be with you shortly

Agent has joined the chat

hello from the agent

how are you doing today

I am good how are you

thanks
5 Conclusion

We presented LPar platform that allows multiple distributed agents to seamlessly work together and deliver a seamless customer experience for Natural Language Interfaces. We also presented two strategies for Agent selection. We also established how these strategies are different from the Master Agent strategy that is currently utilized in most multi-agent systems. With created an experimental setup of Banking domain and showcased how multiple bots of different categories and built over different vendor platforms worked together seamlessly.

6 Future Work

We would like to continue our research in area of Agent allocation and Context retention. We would like to represent the system as a Partially Observable Markov Decision Process and look to leverage advances in Reinforcement Learning to model the state switching.

7 Acknowledgements

I would like to thank following people as without their help this paper would not have net seen light of the day

- Rosy Bharadwaj and Swati Rani for helping create the experimental setup. Really appreciate their efforts and patience for numerous design changes that I kept coming back with. Also, they solved many technical challenges
- Shakeel Khan and Adrian Gubby for always being supportive of crazy ideas which in early days look far from realms of possibility.
- Salil Haridas and Amar Aggarwal for being my mentors at Cognizant.
- My family, as most of this documentation was done at a time which ideally should be given to them

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