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Using Natural Language Understanding for Structured RFQ Negotiation in OTC Markets

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ABSTRACT

This paper presents a novel approach to Request for Quote (RFQ) negotiation in Over-The-Counter (OTC) markets using Natural Language Understanding (NLU) techniques. We propose a system that extracts structured RFQ information from natural language chat messages, addressing the inefficiencies of traditional methods while maintaining the ease of use preferred by traders. Our implementation, based on the Rasa NLU framework, demonstrates promising results in intent recognition and slot filling, with particular challenges noted in currency identification for complex Interest Rate Swap (IRS) specifications. We discuss the system's performance, limitations, and potential improvements, offering insights into the future of AI-assisted financial negotiations.

Keywords: Request for Quote (RFQ), Over-The-Counter (OTC), Natural Language Understanding (NLU), Interest Rate Swap (IRS)

INTRODUCTION

In OTC markets, the negotiation of RFQs traditionally occurs through individual chat conversations between traders and multiple dealers. This process, while familiar to users, is inefficient when negotiating with multiple parties simultaneously. However, structured input methods, such as form-based applications, are often resisted by traders who prefer the flexibility and the speed of natural language communication. To address this challenge, we propose an NLU-based system that can detect RFQ intents and extract relevant parameters from a single string that the users want to copy and paste. This approach aims to combine the efficiency of structured data with the user-friendly nature of conversational interfaces.

BACKGROUND

1. Interest Rate Swaps

Interest rate swaps are a type of derivative financial instrument widely used in over-the-counter (OTC) markets. They allow two parties to exchange interest rate cash flows, typically by swapping fixed-rate payments for floating-rate payments or vice versa, based on a specified notional amount. The most common type is the "plain vanilla" swap, where one party pays a fixed rate while the other pays a variable rate (often tied to LIBOR or another benchmark). Interest rate swaps are primarily used for hedging interest rate risk, speculating on rate changes, or managing cash flows. They're popular among corporations, financial institutions, and governments for various purposes, such as converting floating-rate loans to fixed-rate, or vice versa, to align with financial strategies or market views. The terms of an interest rate swap typically include the notional principal amount (which is not exchanged), the fixed rate, the floating rate reference (e.g., LIBOR), the payment frequency, and the maturity of the swap. These instruments play a crucial role in modern financial markets, with the global interest rate swap market having a notional value in the hundreds of trillions of dollars.

2. Rasa NLU

Rasa NLU (Natural Language Understanding) is an open-source machine learning framework designed for building conversational AI systems. It is a key component of the larger Rasa framework, which also includes Rasa Core for dialogue management. Rasa NLU specializes in intent classification and entity extraction from natural language text, making it particularly useful for developing chatbots and other conversational interfaces. The framework employs a modular architecture that allows developers to combine various NLP and machine learning algorithms, including pre-trained language models, to create custom NLU pipelines tailored to specific use cases. Rasa NLU supports multiple languages and can be trained on domain-specific data, enabling it to understand industry-specific terminology and contexts. It uses a combination of techniques such as intent classification (determining the user's intention from their input) and entity extraction (identifying specific pieces of information from the text). Key features include its ability to handle out-of-scope queries, its extensibility through custom components, and its integration capabilities with various platforms and databases. Rasa NLU's flexibility and scalability have made it a popular choice for both small-scale projects and enterprise-level applications across various industries, including finance, healthcare, and customer service.

RELATED WORK

Constantino et al [1] describes how Natural Language Processing Information Extraction and Expert Systems can be used for reducing the traders qualitative information overload Ade-Ibijola et al[2] describe a system to comprehend and analyze the financial chats retrieved from Instant Bloomberg IB.

Our work builds upon these foundations, specifically addressing the unique challenges of RFQ negotiations in OTC markets.

METHODOLOGY

1. System Architecture

Our system utilizes the Rasa NLU framework, chosen for its flexibility and robust performance in intent classification and entity extraction tasks. The architecture consists of two main components:

1. **Intent Recognition:** Identifies when a user is initiating an RFQ.
2. **Entities:** Extracts specific RFQ parameters from the message.

User types in or pastes a string specifying the quote for the RFQ. This string is sent to Rasa NLU to detect the intent and extract entities for the same. The only intent provided is interest rate swap quote. Based on the provided parameters, it extracts the required parameters. For an interest rate swap, it needs the following info

Currency, floating rate index, fixed rate, notional value of the swap and the tenor. There are multiple other optional fields that can be specified such as payment frequency, day count convention, business day convention and settlement currency.

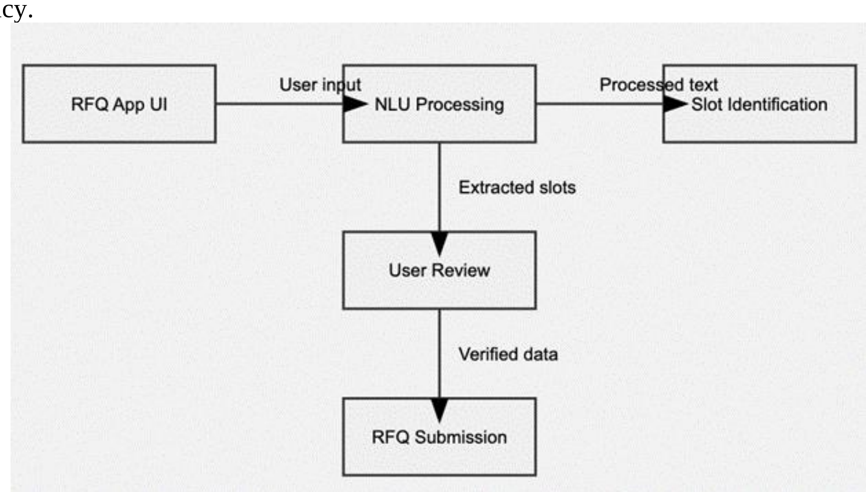

Fig 1: Design of the RFQ input system

3. Data Collection and Preparation

We collected a dataset of 50 example utterances, manually labeled for intents and slots. The dataset covers a wide range of RFQ specifications, with a focus on Interest Rate Swaps (IRS) due to their complexity. This data contains examples with different currencies and with different conventions.

4. Model Training

The Rasa NLU model was trained using our labeled dataset. We employed a combination of supervised learning for intent classification and conditional random fields (CRF) for slot filling.

RESULTS AND ANALYSIS

Our system demonstrated promising performance across various metrics:

Metric	Overall	Intent Recognition	Slot Filling	Currency Identification
Accuracy	0.85	0.92	0.83	0.78
Precision	0.87	0.94	0.85	0.80
Recall	0.83	0.90	0.81	0.76
F1 Score	0.85	0.92	0.83	0.78

The model showed strong performance in intent recognition (F1 score of 0.92), indicating reliable detection of RFQ initiation. Slot filling performance was generally good (F1 score of 0.83), with some variation across different parameter types.

Notably, currency identification proved challenging (F1 score of 0.78), particularly for complex IRS specifications. Users sometimes don't provide some of the assumed parameters like the index currency (6M-Libor) is assumed and is not specified. Sometimes it identifies the frequency in the tenor (5yr) as an index time period. For cross currency swaps, the system was confused as to the notional currency, the currency for the fixed leg vs floating leg and the settlement currency.

DISCUSSION

1. Strengths and Limitations

The system successfully extracts structured RFQ information from natural language inputs in many cases, potentially streamlining the negotiation process. However, performance degrades with vague or incomplete specifications, reflecting the inherent challenges of natural language processing in specialized domains.

2. Proposed Improvements

To address current limitations, we propose:

1. Expanding the training dataset, particularly for challenging cases like complex currency pairs.
2. Implementing a more sophisticated dialogue management system to handle ambiguities and missing information.
3. Incorporating domain-specific knowledge bases to enhance entity recognition, especially for financial instruments and currencies.
4. Providing a summary of the system recognized values and allowing the user to correct the values before submission and using the corrected data for training and improving the model.

CONCLUSION

Our NLU-based approach to RFQ negotiation demonstrates the potential for AI to bridge the gap between user-friendly interfaces and efficient, structured data processing in financial markets. While challenges remain, particularly in handling complex specifications, the system shows promise in streamlining OTC market operations. Future work will focus on refining the model's performance and expanding its capabilities to cover a broader range of financial instruments and negotiation scenarios.

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