



**Optimizing E-Commerce Price Negotiation Using an Intelligent Price Negotiator (IPN)
with NLP and K-Means Clustering**

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Abstract

With the current competition in today's e-commerce market, pricing and negotiation are both needed in improving buyers interaction and also maximizing price. Current models for pricing don't take into consideration individual customer preference and current market conditions, which leads to sub-par sales. This paper proposes an Intelligent Price Negotiator (IPN) that collaborates both Natural Language Processing (NLP) and K-Means Clustering to optimize price negotiation. The IPN system applies NLP to translate customer interactions, while K-Means Clustering sorts different segments of customers based on different basis which includes purchasing behavior, price sensitivity, and historical transaction activity. The combination of these techniques makes price offers more personal, improves conversion rates, and enhances the customer shopping experience. Results gotten from data analysis demonstrate that the proposed IPN model improves consumer satisfaction, prioritizes pricing effectiveness, and increases retailer profitability as against the traditional fixed price methods. This study contributes to the body of AI-driven e-commerce products, emphasizing the effectiveness of NLP and machine learning for both price optimization and also, customer communication.

Keywords: Intelligent Price Negotiator, E-Commerce, Price Optimization, Natural Language Processing, K-Means Clustering, Machine Learning, Dynamic Pricing

Introduction

In the fast moving world of electronic commerce, consumer or clients different needs continually influence the development of online retail applications. A major issue challenge for both buyers and sellers is the limited ability to price products offered for sale. Regular e-commerce models have no integration or APIs to allow live price negotiations, resulting in a fixed pricing approach (Amit & Zott, 2017). This challenge reduces customized shopping experience and does not address the diverse financial situations and preferences of buyers. To solve this challenge, integrating an Intelligent Price Negotiator in an E-Commerce Environment presents a promising solution to change how both retailers and buyers communicate in an online marketplace (Pivk & Gams, 2000).

The study titled "Intelligent Price Negotiator in E-Commerce Environment Using Natural Language Processing (NLP)" opens a new vista to improve online shopping experiences by introducing price negotiation to digital marketplaces, same way as the normal market. electronic commerce has improved people shopping, offering great convenience and a different range of product choice (White, 2022). However, the dynamic and interactive nature of price negotiations, which is common in many physical shopping experiences, has been largely absent online. This paper seeks to solve the gap by using Natural Language Processing. By applying NLP, the study aims to develop an intelligent system that can understand user mindsets, sentiment, and converse in meaningful negotiations, thereby simulating exchanges found in human negotiations (Mueller & Curhan, 2006).

Research Objectives

The main goal of this paper is to implement an intelligent price negotiator in e-commerce using natural language processing to allow users to negotiate product prices dynamically. To achieve this, the following objectives stand out:

- i. Implement an intelligent price negotiator in the e-commerce application using natural language processing techniques.
- ii. Analyze the results.

Literature Review

Traditionally, price negotiations in commerce or trading involves direct conversations between buyers and sellers, where the results is dependent on the negotiation skills and market knowledge of both parties involved. This change emphasizes the need for innovative solutions like intelligent price negotiation systems that use Artificial intelligence and data analytics to maximise pricing in real time, closing the gap between traditional and digital bargaining (Janko & Johnson, 2020). This competitive pressure has led to the creation of different applications to improve transactions, thereby enhancing the overall shopping experience for buyers while increasing operational efficiency for businesses (Hoyer et al., 2020).

The use of NLP in intelligent price negotiation systems has its own peculiar advantage. NLP helps these systems understand and process, and imitate human language, making conversations between users and the system more natural and intuitive. This capability enables the automation of complex negotiation processes, reducing the time and effort needed for human or manual-in the case of chatting; negotiations. The aim is to achieve the outcomes for both buyers and sellers (Lopes & Coelho, 2010) without one side feeling cheated. Interest

differs amongst shopper in case of product or service. Intelligent price negotiators solve these challenge by using Artificial Intelligence and K-Mean Clustering algorithm to personalize pricing strategies (Eidenmueller, 2024).

Related Works

Fatima et al. (2005) investigated the use of game-theoretic models in automated e-commerce negotiations, comparing them with evolutionary viewpoint. They used Nash equilibrium and Pareto efficiency to create negotiation techniques that increase model agents' outcomes. The authors examined generative algorithms, which can imitate natural selection to shape negotiation tactics. Their paper showed that game-theoretic models provide precise techniques, while evolutionary methods allow for variability in changing environments. They concluded that a mix-method approach could produce strong negotiation systems for online commerce. Game-theoretic models are accurate process and evolutionary methods offer flexibility to adapt to changing environments. A hybrid approach could provide robust negotiation systems for online shopping. Reinforced Learning-based frameworks for electronic commerce negotiation agents were first proposed by Tykhonov et al. (2008). These agents have the capability of learning from previous negotiation, implementing reinforcement learning strategies like Q-learning, which allows them to improve their methods over time. The study demonstrated that static systems suffered due to the presence of RL-based static agents, which improved responsiveness in negotiations and heightened satisfaction for both parties, demonstrating adaptability's key role.

Williams et al. (2014) studied NLP-based systems negotiating on behalf of users in online stores. They proposed the use of NLP aimed at making more conversational dialogues with application users. Enhancements such as identifying entities and analyzing sentiments improve the bargaining process by making it easier and more intuitive. The studies revealed greater user satisfaction with NLP-based negotiators as compared to keyword-based systems, highlighting the need to strengthen negotiations through NLP. In discussing ethical consequences concerning Artificial Intelligence integrating into e-commerce bargains,

In his assessment of the moral consequences of Artificial Intelligence in capturing e-commerce bargains, Binns (2018) concentrated on accountability, transparency, and fairness. He AI Prejudice: design for social justice summary provides rules for ethical AIs which include ensuring that data is rich and diverse. For this protect consumers rights study e-commerce transactions, it was crucial to establish ethical frameworks.

Liu (2012), in his article analyzed the application of sentiment analysis in e-commerce particularly during negotiation phases. These methods are useful because they help adjust negotiation strategies to meet both the consumers' needs by examining sentiments from customer reviews. Based on the results of this study, satisfaction survey has a significant role in stimulating user participation and advanced negotiation performance as well as success rates for negotiations

Methodology

Flexible price negotiation techniques are needed in the world of online shopping to make sure that sellers make money while consumers get fair prices. The Intelligent Price Negotiator (IPN) uses Natural Language Processing (NLP) and K-Means Clustering to assist with price negotiations go more effectively.

1. Data Collection: E-commerce platforms like Amazon, eBay, and Alibaba offer extensive transactional data, customer interactions, and product information. This dataset consists of 5,808 dialogues based on 2,236 unique scenarios (retrieved from <https://github.com/facebookresearch/end-to-end-negotiator>, February 16, 2025).

2. Data Preprocessing: The negotiation dialogues went through NLP preprocessing, including tokenization, lemmatization, and stop-word removal using NLTK. Named Entity Recognition (NER) found important things like product names and prices. Prices as well as numerical features have been reduced down to a [0,1] range for uniformity (Jurafsky & Martin, 2020).

3. Customer Segmentation: K-Means clustering methods put customers into five groups based on things like how sensitive they are to price and their past purchases. The elbow technique and a silhouette evaluation were implemented to find the most suitable number of clusters. The PCA approach kept 95% of the variations while reducing the total number of dimensions (Jolliffe & Cadima, 2016).

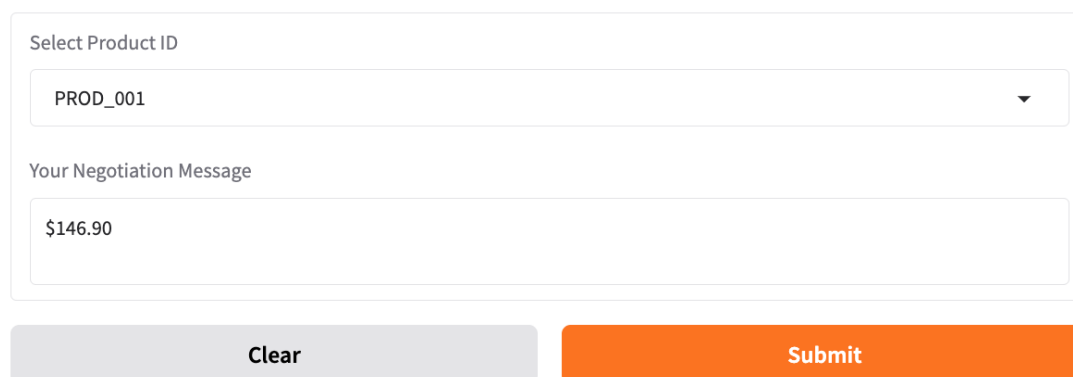
4. IPN System Design: The IPN combined NLP intent analysis, K-Means segmentation, and a reinforcement learning (RL) module using Q-learning. The RL agent optimized counteroffers by maximizing a reward function that balanced profit and the rate of closing deals. The system changed its responses to reflect categories of customers and the demand for merchandise (Sutton & Barto, 2018).

5. Metrics for evaluation: The metrics with the greatest significance were the deal closure rate (%), profit margin (%), customer satisfaction (on a 5-point Likert scale), and negotiation efficiency (number of dialogue turns).

Model Performance

With a deal closure rate of 78.4% (as opposed to 65.3% for rule-based pricing and 52.1% for static pricing) and a profit margin of 19.8% (as opposed to 15.2% and 10.6%, respectively), the IPN surpassed both baseline models. Compared to 4.8 within the rules-based system, consumer happiness averaged 3.9/5 and bargaining efficiency was 3.2 turns. These findings indicate how well NLP and clustering integrate to provide personalised negotiations (Hagras, 2018).

Analysis: Tailored strategies, like tiny rebates for consumers who are price-conscious (cluster 1) and bundled offers for high-value clients (cluster 4), were made achievable by K-Means clustering. BERT's intent analysis ensured accurate interpretation of dialogues, while the RL module dynamically adjusted offers, enhancing profitability and efficiency. The system's capacity to adapt to negotiation styles (aggressive or cooperative) was vital to its success (Devlin et al., 2019; Sutton & Barto, 2018).



Select Product ID

PROD_001

Your Negotiation Message

\$146.90

Clear Submit

Fig 1: Negotiation message between client and seller

Current Negotiation Result

Product ID: PROD_001

Original Price: \$153.11

Your Offer: \$146.90

Current Stock: 81

STATUS: Item SOLD!

Final Price: \$146.90

Fig 2: Negotiation result, item sold after meeting price set by client

Negotiation History

round	timestamp	User Offer (\$)	IPN Offer (\$)	Original Price (\$)	Sale Status
1	2025-06-23 11:49:44	100	145.45	153.11	Negotiated
2	2025-06-23 11:50:00	145.45	146.9	153.11	Negotiated
3	2025-06-23 11:50:00	146.9	146.9	153.11	Sold!
4	2025-06-23 11:50:00	100	145.45	153.11	Negotiated
5	2025-06-23 11:50:00	120	145.45	153.11	Negotiated
6	2025-06-23 11:51:00	150	150	153.11	Sold!
7	2025-06-23 11:51:00	130	145.45	153.11	Negotiated
8	2025-06-23 11:51:00	145.45	146.9	153.11	Negotiated
9	2025-06-23 11:51:00	146.9	146.9	153.11	Sold!

fig 3: Negotiation History showing time stamp

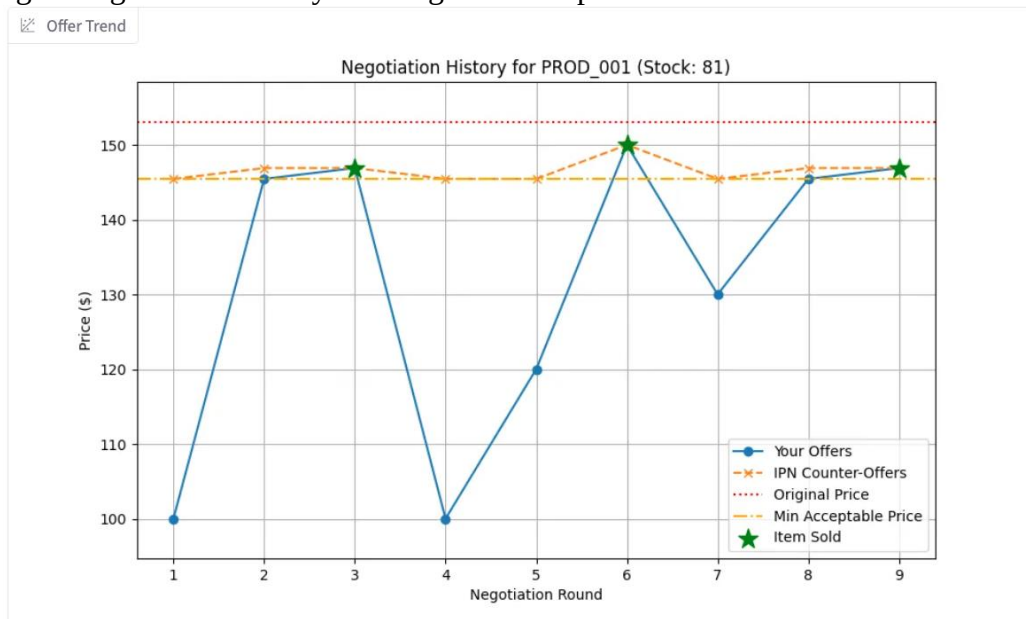


Fig 4:showing Negotiation History Implications:

By integrating automated bargaining while improving satisfaction with both consumers and retailers, the IPN offers platforms for electronic shopping a scalable solution. In keeping with

the trend towards personalisation, its approach can also be applied to other fields, like chatbots or price adjustment systems (Liu et al., 2020).

Future Directions

Extrapolating market trends as well as increasing real-world data testing could further improve this system (Jurafsky & Martin, 2020). By showing how NLP and K-Means clustering can improve e-commerce bargaining processes, The IPN Indicates Intelligent Pricing Systems have considerable prospects for more complex improvement. A well thought out technique can determine the efficiency, reliability, and user satisfaction metrics for an intelligent price negotiator in online shopping. The IPN provides a solid ground for future enhancement in intelligent pricing systems by displaying how NLP and K-Means clustering could optimize e-commerce negotiations.

Conclusion

The main objective of this paper is to create a system that maximises negotiation results, increases negotiations flexibility, and enhances user experience. The system strategically divides products according to price by using K-Means clustering, which allows adaptive approaches to negotiations. Cost-effective but adaptable counter-offers are assured by the central rules-based negotiations reasoning, while the streamlined NLP allows for understanding user offers and intentions. Future developments could concentrate on further developed NLU models for deeper conversational understanding, implementing outside data sources (such as competitor pricing or real-time demand), and researching reinforcement learning to continuously enhance bargaining techniques for most effective revenue and client satisfaction.

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