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Research on Customer Emotion Recognition on the Side of State Grid Power Customer Service Agents based on Large Language Models

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Abstract

In the service scenarios on the side of power customer service agents, it is difficult for agents to accurately capture and respond to changes in customer emotions, resulting in poor service experience. Fluctuations in customer emotions directly affect their communication methods and expression of needs. To address this problem, this paper proposes a three-stage emotion recognition and response scheme of "small model pre-screening - large model emotion grading - recommended soothing scripts". Firstly, a domain-specific sensitive lexicon for power customer service is constructed, and a lightweight small model is adopted to achieve rapid sensitive word recognition. If a sensitive word is matched, manual agent intervention is triggered and the call is transferred to a manual agent. Secondly, based on the State Grid Guangming Large Model, the model is fine-tuned to build an emotion recognition model, which judges the emotional polarity (positive, neutral, negative) of the dialogue text after the manual agent is connected, and subdivides negative emotions into three levels: mild, moderate, and severe. Finally, according to the recognition results of different levels of negative emotions, soothing scripts are recommended to assist agents in making accurate responses. This can effectively improve the efficiency of agents' emotion perception and response speed, enhance customer experience, and provide corresponding technical support for the intelligent upgrading of power customer service.

Keywords

Customer Service; Emotion Recognition; Large Language Model; Online Agent; Model Fine-tuning; Script Recommendation.

1. Introduction

1.1. Research Background

With the rapid development of the power industry and the continuous improvement of customer service needs, the 95598 State Grid Power Customer Service has become an important bridge between power supply enterprises and users, undertaking business functions such as fault repair, business consultation, complaint handling, and service supervision. In recent years, with the popularization of online customer service channels, the number of customer consultations received by online agents has increased sharply. In the current customer service scenarios, it is difficult for agents to accurately capture and quickly respond to changes in customer emotions, leading to poor service experience. Fluctuations in customer emotions directly affect their communication methods and expression of needs, while existing systems lack real-time and accurate emotion recognition capabilities. Therefore, realizing real-time recognition of customer emotions and providing customer emotion response strategies can effectively avoid emotional escalation, which is of great significance for improving service quality and customer satisfaction[1-5].

1.2. Related Research

In recent years, with the rapid development and application of large models, various industries and fields have also integrated large models into their business functions, striving to improve customer experience and business efficiency. Research related to the field of power customer service is also constantly expanding and deepening[6].

2. Research Methods and Research Content

2.1. Definition of Emotion Classification

According to the characteristics of the online State Grid text-based power customer service scenarios, this paper divides customer emotions into three categories: positive, neutral, and negative, with specific definitions as follows[7]:

Positive Emotion: Customers express satisfaction, gratitude, or praise for power services. For example, "Thank you very much for handling the power outage problem in a timely manner; the service is really good!"

Neutral Emotion: Customers express objective consultations, inquiries, or statements without obvious emotional tendencies. For example, "What is the electricity fee standard for residential users this month?"

Negative Emotion: Customers express dissatisfaction, complaints, anger, or anxiety about power services. For example, "The power has been out for three hours, and no one has come to repair it. What's going on?"

For negative emotions, it is necessary to distinguish the emotional intensity: mild, moderate, and severe[8].

2.2. Research Content

2.2.1. Construction of Sensitive Lexicon

The construction, establishment, and maintenance of a sensitive lexicon: Sensitive words in customer consultations in the power field have unique professional characteristics. Intelligently constructing and dynamically maintaining a sensitive lexicon can improve the accuracy of emotion recognition. Sensitive words for negative emotions specifically include: angry, disappointed, anxious, dissatisfied, speechless. Such events may involve emergency situations related to personal safety and the stable operation of the power grid, requiring urgent and rapid handling. Words suspected of media exposure include: media exposure, Douyin, Kuaishou, etc. When users mention such words, it may involve high-risk demands from users. To avoid affecting service efficiency and customer satisfaction, please intervene and handle them as soon as possible[9].

2.2.2. Construction of Sensitive Word Matching Small Model

The construction of a small model to match the sensitive lexicon for sensitive word recognition: Firstly, query whether the consulting customer has a call record in the past 24 hours. If there is a call record but no sensitive word conversation within 24 hours, during the text customer service consultation process, the small model real-time recognizes sensitive words or service taboos in customer service. If a sensitive word is triggered, the call is directly transferred to a manual agent. If there is a call record within 24 hours and the conversation semantics contain sensitive words, the call is directly transferred to a manual agent after the text customer service conversation is connected[10].

When a customer consults the customer service online, cosine similarity is used to detect whether the customer has a call record in the past 24 hours that can be matched with sensitive words. If a sensitive word is matched, the call is directly transferred to a manual agent; if no sensitive word is matched, real-time monitoring is performed, and once a sensitive word is matched, the call is directly transferred to a manual agent. As shown in Figure 1 Sensitive Word Matching Device.

Cosine Similarity is a method to measure the similarity between two vectors. It represents the similarity by calculating the cosine value of the angle between two vectors. The value range of cosine similarity ($cos\theta$) is $[-1, 1]$, where -1 represents no similarity and 1 represents very high similarity.

Cosine Similarity Formula:

$$Similarity = cos\theta = \frac{A \cdot B}{|A||B|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}}$$

2.3. Construction of Emotion Recognition Model

2.3.1. Data Collection

The data in this study are derived from the text customer service chat records of State Grid Customer Service, with a collection time range from January 2025 to June 2025. To ensure the representativeness and diversity of the data, a stratified sampling method was adopted for data collection. The original data were strictly desensitized to remove user identity information and sensitive content, and a total of about 5,000 conversation fragments were collected.

2.3.2. Data Preprocessing

Data preprocessing is a key step to improve model performance. This study mainly includes the following operations:

Text Cleaning: Remove irrelevant symbols, correct typos, and standardize expressions;

Dialogue Segmentation: Take "user-customer service" turn as the minimum unit and retain the dialogue context;

Language Filtering: Only retain Chinese dialogues to ensure language consistency.

After preprocessing, a final valid dataset of 4,000 entries was obtained for subsequent emotion annotation and model training.

2.3.3. Data Annotation

Data annotation is the cornerstone of building a high-quality emotion recognition model. To achieve accurate recognition of user emotions in customer service texts, this study designed and implemented a two-stage hierarchical annotation system. This system first performs coarse-grained emotion classification, and then conducts fine-grained division of the intensity of the identified negative emotions.

First Level: Three-Class Basic Emotion Classification

Positive: Users express gratitude, satisfaction, praise, or joy. For example: "The problem has been solved, thank you very much", "Okay, thank you very much"

Neutral: Users make factual statements, information inquiries, or process confirmations without obvious emotional tendencies. For example: "I want to check my electricity usage this month", "How much is left in my electricity bill"

Negative: Users express any form of dissatisfaction, frustration, or anger.

Second Level: Three-Level Division of Negative Emotion Intensity

Mild Negative: Express slight distress, helplessness, or suggestions with a relatively mild tone. Usually includes phrases such as "a bit troublesome", "hope to improve", "not very convenient". For example: "The power has been out for an hour; please check it quickly"

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Moderate Negative: Express clear dissatisfaction and complaints with obvious emotional release, possibly accompanied by urging or questioning. Commonly used expressions such as "very disappointed", "too inefficient", "why hasn't it been handled yet". For example: "I've been waiting for a day; why hasn't the power come back"

Severe Negative: Intense accusations, anger, including extreme expressions or threatening tendencies. For example: "If it's not handled, I will complain to the end", "It's simply irresponsible; I must get an explanation", "The power has been out all day with no one caring; it's too much"

2.3.4. Large Model Fine-tuning

To optimize the model fine-tuning effect, the following fine-tuning parameters were determined through experimental comparison:

Table 1. Model comparison

Parameter Name	Parameter Value	Parameter Description
batch size	16	Number of samples per training iteration
Learning Rate	2e-5	Cosine annealing learning rate scheduling strategy is adopted, with an initial learning rate of 2e-5
epochs	10	Number of training rounds; early stopping strategy (patience=3) is adopted to prevent overfitting
dropout rate	0.1	Add a dropout layer in the fully connected layer to prevent model overfitting
Optimizer	AdamW	Weight decay coefficient is 1e-4
Loss Function	Cross-Entropy Loss Function	Loss function suitable for multi-classification tasks

Based on the above fine-tuning parameters, the State Grid Corporation's Guangming Large Model is fine-tuned, and the fine-tuned model is used to build the emotion recognition agent.

2.3.5. Emotion Recognition Agent

After transferring to a manual agent, for the emotion recognition rules, a background management switch is added to control whether the model is called. A foreground management switch is also added to support enabling emotion recognition capabilities for different provinces and agents. If the corresponding switch is turned on, for the enabled provinces and agents (agent switches are identified by agent IDs), the large model is called for emotion recognition in all conversations; if the corresponding switch is not turned on, the emotion recognition large model is only called for conversations where the customer has called three or more times within 24 hours, i.e., starting from the customer's third call within 24 hours.

Emotion recognition is performed based on the large model, with the following prompt template:

Role and Task Definition

You are an emotion recognition expert in the power customer service field. Based on the dialogue text between power customers and manual agents, you need to complete two core tasks: 1) Emotional polarity judgment (positive / neutral / negative); 2) Negative emotion grading (mild / moderate / severe).

Recognition Rule Explanation

Emotional Polarity Judgment Standards:

Positive Emotion: Contains positive expressions such as gratitude, satisfaction, and recognition (e.g., "Thank you, the problem was solved in a timely manner", "Your service is really professional");

Neutral Emotion: Only consults about business or states facts without obvious emotional tendencies (e.g., "How to check electricity bills", "The power is out; when will it come back");

Negative Emotion: Contains negative expressions such as complaints, dissatisfaction, accusations, and anxiety (e.g., "Waited for more than an hour and it's still not solved", "Repeated errors are ridiculous", "The power outage has affected normal life").

Negative Emotion Grading Standards:

Mild Negative: Slight complaints without strong emotional expressions, only mentioning the impact of the problem (e.g., "This operation is a bit troublesome", "The response was a bit slow");

Moderate Negative: Clearly expresses dissatisfaction with a certain degree of emotional release, requiring prompt handling (e.g., "Reported multiple times but not resolved; very disappointing", "Such a simple problem requires repeated communication");

Severe Negative: Intense accusations, anger, including extreme expressions or threatening tendencies (e.g., "If it's not handled, I will complain to the end", "It's simply irresponsible; must get an explanation", "The power has been out all day with no one caring; it's too much").

Output Format Requirements

Directly return the recognition result without additional explanation, in JSON format as follows:

```
{
  "polarity": "positive/neutral/negative",
  "negative_intensity": "none/mild/moderate/severe",
  "confidence": 0.95,
  "key_evidence": ["Key original sentences or words supporting the judgment"]
}
```

3. Design and Recommendation of Soothing Scripts

According to different scenarios and different levels of negative emotions, different soothing scripts are recommended for agents.

For example, in the scenario of power outages caused by severe weather with a long duration:

Recommended script for mild negative emotions: "We apologize. Due to the continuous high temperature/cold wave weather, the air conditioning load has surged sharply, resulting in widespread overloading of power supply facilities and multiple faults. All our maintenance personnel are working on-site for repairs. However, due to the large number and wide distribution of fault points, it takes a certain amount of time to repair them one by one. Please understand; we believe the power supply will be restored as soon as possible. During the disaster: 1. We apologize. Due to the current weather conditions, it is likely to cause significant risks to the personal safety of maintenance personnel, and the fault site does not have the conditions for repair temporarily. Please wait patiently. Once the site is ready for repair, we will arrange maintenance immediately and strive to restore power supply for you as soon as possible. Thank you for your understanding and support."

Recommended soothing script for moderate negative emotions: "Please don't worry. Thank you very much for your understanding. From your words, we can tell that you are a reasonable person who can understand the situation of our on-site staff. Moreover, you are very professional, worrying about their safety, knowing that working in rainy or severe weather will pose safety hazards. Please rest assured; we will carry out the repair as soon as possible and

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restore power supply for you. Thank you again for your support and understanding of our work!"

Recommended soothing script for severe negative emotions (when the customer insists on not accepting): "I can understand that the power outage has caused unnecessary trouble for you. Thank you very much for your valuable suggestion. We will reflect it to the higher authorities. It is because of suggestions like yours that we can continuously improve."

4. Conclusion

Through sensitive word matching, customers who may have negative emotions are initially screened out; the large model is used to quickly and efficiently recognize customer emotions. The power field also has its own unique characteristics in customer service. For example, when a power outage occurs, the number of consulting customers may surge, and the pressure on customer service agents will also increase sharply. At this time, based on the emotion recognition results, negative emotions of customers are graded, assisting agents in quickly determining solutions, which greatly relieves the pressure on agents and improves customer experience.

Addressing the pain point that State Grid power customer service agents struggle to accurately capture customer emotions, this study proposes a three-stage solution of "small model pre-screening - large model emotion grading - recommended soothing scripts", providing a practical technical path for the intelligent upgrading of power customer service. Through the synergistic effect of sensitive lexicon construction and lightweight small models, rapid identification of high-risk customers and accurate transfer to manual agents are realized, which effectively shortens the response cycle for urgent demands and avoids conflict escalation caused by delayed handling due to emotional factors. The emotion recognition model built based on the fine-tuning of the State Grid Guangming Large Model, relying on a two-stage hierarchical annotation system and optimized fine-tuning parameters, not only achieves accurate classification of positive, neutral, and negative emotions but also subdivides negative emotions into three levels: mild, moderate, and severe, providing data support for differentiated responses.

In practical application scenarios, this solution demonstrates significant practical value and scenario adaptability. Power services have strong people's livelihood attributes, and emergencies such as power outages and faults are prone to cause customer emotional fluctuations. Especially in scenarios such as severe weather and peak electricity consumption periods, the number of customer service consultations surges, and agents face enormous pressure. Through automated emotion recognition and script recommendation, this solution helps agents quickly grasp the customer's emotional state without spending extra energy to judge emotional tendencies, and can directly conduct targeted communication based on the recommended scripts. This not only improves the efficiency of service response but also ensures the professionalism and empathy of communication, effectively alleviating the work pressure of agents. At the same time, the dynamic maintenance mechanism of the sensitive lexicon and the flexible switch setting of the emotion recognition model enable it to adapt to the personalized needs of different provinces and different business scenarios, with good scalability and operability.

From the perspective of industry development, this study deeply integrates large language models with power customer service scenarios, breaking through the limitation of traditional customer service systems of "passive response" and constructing a new service model of "active identification - intelligent grading - accurate response". The emotion annotation dataset in the power field, optimized model fine-tuning strategies, and scenario-based soothing script library accumulated during the research process provide valuable practical experience and data

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support for subsequent related research. In the future, the multimodal emotion recognition capability can be further expanded by integrating non-text features such as speech intonation and dialogue rhythm to improve the comprehensiveness and accuracy of emotion recognition. At the same time, combined with customer portrait data to realize personalized customization of soothing scripts, promoting the upgrading of power customer service from "standardized service" to "personalized service", continuously improving customer satisfaction and brand trust, and injecting new momentum into the high-quality development of customer service in the power industry.

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