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Full-length article

Key technologies of artificial intelligence in electric power customer service

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Abstract: As the demand for customer service continues to increase, more companies are attempting to apply artificial intelligence technology in the field of customer service, enabling intelligent customer service, reducing customer service pressure, and reducing operating costs. Currently, the existing intelligent customer service has a limited degree of intelligence and can only answer simple user questions, and complex user expressions are difficult to understand. To solve the problem of low accuracy of multi-round dialogue semantic understanding, this paper proposes a semantic understanding model based on the fusion of a convolutional neural network (CNN) and attention. The model builds an “intention-slot” joint model based on the “encoding–decoding” framework and uses hidden semantic information that combines intent recognition and slot filling, avoiding the problem of information loss in traditional isolated tasks, and achieving end-to-end semantic understanding. Additionally, an improved attention mechanism based on CNNs is introduced in the decoding process to reduce the interference of redundant information in the original text, thereby increasing the accuracy of semantic understanding. Finally, by applying the model to electric power intelligent customer service, we verified through an experimental comparison that the proposed fusion model improves the performance of intent recognition and slot filling and can improve the user experience of electric power intelligent customer services.

Keywords: Artificial intelligence, Electric power customer service, Intelligent customer service semantic understanding, Fusion model.

0 Introduction

Traditional manual customer service requires a large number of customer service personnel to invest in 7×24 h of customer service operations. However, owing to the repetitiveness and singularity of customer service work, customer service personnel are prone to boredom and negative emotions; the overall job mobility of customer service work is very large, easily resulting in low customer service efficiency, and its service quality is frequently difficult to control, resulting in generally high operating costs. Additionally, with the continuous expansion of user scale and continuous improvement in service quality requirements, the limited customer service capabilities increasingly fail to satisfy increasing customer service requirements. At this stage, the development of customer service has entered a bottleneck.

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With the continuous development of artificial intelligence (AI) technology, the “AI + X” application paradigm has gradually matured. AI technology has rapidly penetrated all aspects of life and has a profound impact on many fields such as medical care, transportation, manufacturing, and security, and breakthrough results have been achieved. For example, in call centers, intelligent robots are used to replace manual customer service to complete many simple and repeatable services to provide customers with a more high-quality and efficient service experience. The existence of such advantages has resulted in the emergence of intelligent customer service and its continuous development and expansion.

Currently, industries such as finance, communication operators, and e-commerce retail are gradually beginning to deploy and develop the construction and application of intelligent customer service robots, intelligent voice portals, and online customer service systems. The development of AI applications in the field of customer service services is relatively mature, but current intelligent customer service systems are not sufficiently accurate to understand customers’ intentions, and the user experience is very unsatisfactory. Thus, this paper proposes a language-understanding model based on the fusion of convolutional neural networks (CNNs) and attention. This model attempts to improve the ability of the intelligent customer service system to understand customers’ intentions to understand more accurately the requirements of users and improve user experience. An experiment of electric power customer service was conducted to prove the effectiveness of the proposed method.

1 Related Studies

Extensive related research has been conducted on the construction of joint models of intent recognition and slot filling. For example, Xu et al. proposed a CNN model based on TriCRF, which automatically extracts features from CNNs and shares them in the two tasks of intent recognition and slot filling [1]. However, for the sequence labeling of sentences, this method often lacks the ability of long-term memory. Therefore, to solve this problem, researchers have used gated loop units (GRUs) to learn the representation of each time step, predict the value of each slot, and subsequently use a pooling layer to capture the global characteristics of sentence intent. Liu et al. and Ma et al. both introduced an attention mechanism into the recurrent neural network (RNN) structure to provide additional feature information for slot and intent prediction[2, 3]. Hakkani-Tür et al. proposed the bi-directional long short-term memory (BLSTM) to predict word labels by capturing the dependence of related terms and context information[4].

Through experiments, Yin et al. observed that a CNN has certain advantages for target recognition tasks, while an RNN has certain advantages for sequence recognition modeling owing to its unique memory function[5]. Compared with RNNs, the advantage of a conditional random field (CRF) is that it calculates the joint probability of the entire sequence label, which can optimize the entire sequence instead of splicing the optimal label at each moment. Based on the above research, Hua et al. constructed a joint model of intent recognition and slot filling by connecting the output vector of a BLSTM and CNN and feeding it back to the CRF layer [6]. Qin et al. proposed a stack-propagation framework based on token level, which directly used the output of intent recognition as the input of the slot filling task, and not only directly used the intent information to guide the slot filling task [7]. And in the final experimental stage, the role of intent for slot filling is visualized by designing experiments with oracle intent information to improve the interpretability of the model. Based on the abovementioned research, this paper introduces the BLSTM–CNN–CRF model proposed by Hua et al., the attention-based recurrent neural network model proposed by Liu et al. and the stack-propagation model proposed by Qin et al. And Comparing the same test data and the same experimental environment the experimental effects of the joint modeling of each model in the electric power customer service dialogue domain.

Currently, industries such as finance and communication have also conducted relevant research on intelligent customer service. Through continuous exploration in recent years, Tencent smart customer service observed that the problem that smart customer service products often appear less intelligent can be better solved through human–machine collaboration [8]. Li et al. studied the application of intelligent customer service in the securities industry, using deep learning technology and massive resource data to realize online intelligent customer service and intelligent voice navigation [9]. Li et al. used speech recognition, natural language processing, background knowledge base management, and speech synthesis technology to effectively reduce labor costs and improve China Unicom’s service efficiency and user customer service experience [10]. Mei et al. built a knowledge base based on the knowledge graph, analyzed and studied the application of intelligent technology in the field of railway customer service, and designed an intelligent customer service system solution for the railway 12306 line, which reduced the pressure of manual customer service and improved users’ personalized service experience [11]. Xiao et al. introduced an intelligent customer service system, organically integrated the system architecture and station networking scheme, and discussed the application scheme of intelligent speech recognition technology in the intelligent customer service system [12].

In summary, the current research on intelligent customer service mostly uses AI technologies such as speech recognition, natural language processing, and knowledge graphs. Combining their business needs, they use massive data and effective models to design corresponding intelligent customer service systems. This can effectively reduce labor costs, increase employee work efficiency, and effectively improve user experience. Therefore, the research described in this paper aimed to solve the problem of low accuracy of semantic understanding in the multi-round dialogue of intelligent customer service. Based on previous studies, a semantic understanding model based on the fusion of a CNN and attention is proposed, and it is expected to be optimized through the design of the model and to enhance the user experience of intelligent customer service dialogue systems.

2 Key technologies of intelligent customer service

2.1 Machine learning

Machine learning is the core of AI. It is a multi-field cross-discipline that studies algorithms from data. It studies how computers simulate or realize human learning behaviors, and select algorithms and build models based on existing data or past experience, and finally predict new data and reorganize the existing knowledge structure iteratively to improve their performance. The core of machine learning is data, algorithms (models), and computing power [14-17].

2.2 Automatic Speech Recognition

Speech recognition refers to the technology that converts speech into language and text through a series of technologies [18-22]. Speech recognition technology first uses pattern recognition technology to extract features, train models and test applications on prepared data. The data must be preprocessed in the data preparation stage, and then a feature model is obtained through signal processing and feature extraction. Finally, a neural network algorithm is used for repeated learning and training to obtain the acoustic and language models, and the scores of both the acoustic and language models of the target test speech data are obtained. Additionally, the candidate search algorithm is used to obtain the result of recognition. The accuracy of speech recognition directly affects the accuracy of understanding user intentions of an electric power intelligent customer service.

2.3 Text-to-speech

Text-to-speech (TTS) refers to the technology that generates artificial speech through mechanical and electronic methods to convert arbitrary input text into corresponding speech [23-29]. TTS enables the integration

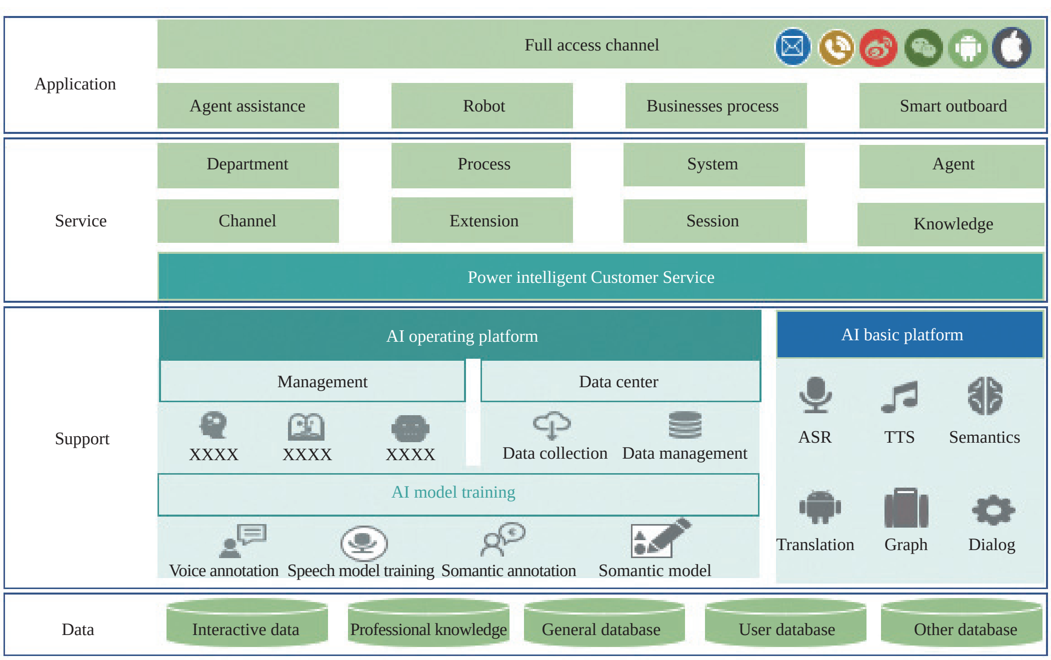

Fig. 1 Electric power customer service application framework

of data communication and voice communication in a terminal. By converting the information provided by the user in text mode to voice output, it significantly facilitates terminal users and improves the experience of smart customer service users.

2.4 Knowledge graph

The knowledge graph is essentially a large-scale semantic network that primarily describes the conceptual entity events of the objective world and the relationships between them [38-44]. The question-and-answer (Q&A) system of intelligent customer service determines the corresponding answer according to a customer's question, and the answer is a knowledge and an entity, and the knowledge graph is based on graph relations to construct the knowledge into the ontology and construct the knowledge base containing domain knowledge [45-46].

2.5 Semantic understanding

Semantic understanding is the key technology of intelligent customer service systems, which can be divided into semantic understanding based on language rules, machine learning methods based on statistical principles, and end-to-end semantic understanding. Among them, semantic understanding refers to the use of various machine learning modeling methods to learn and understand the semantic content represented by a text. In human–machine dialogue systems, semantic understanding is primarily composed of two subtasks: intent recognition and slot filling. Intent recognition is the process of analyzing user input information and identifying user intent, which is a classification problem. Slot filling is the process of filling in the information by filling a slot, that is, converting the user's implicit intention into explicit instructions for the computer to understand, which is a sequence labeling problem. Slot information can be considered a parameter corresponding to an intent, and one intent may correspond to multiple slots.

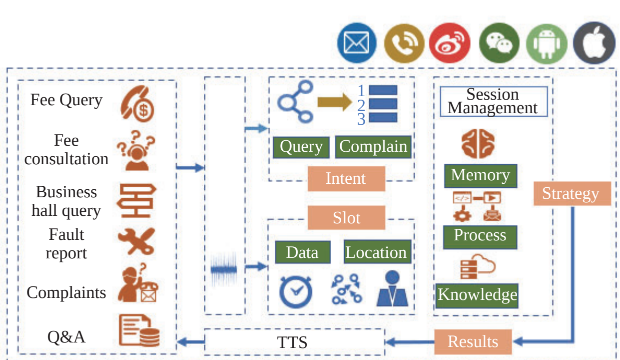

Fig. 2 Smart customer service workflow

3 System Architecture of Power Smart Customer Service Application

Intelligent customer service is an industry-oriented technical method developed based on large-scale knowledge processing. It primarily establishes a rapid and effective communication between enterprises and a large number of users based on natural language processing [47].

Using the intelligent customer service system in the electric power industry as an example, the overall framework of the intelligent customer service system is shown in Fig. 1. The entire system is crudely divided into four parts: data layer, support layer, service layer, and application layer.

(1) Data layer. The data layer provides support for the data analysis and processing of the upper AI platform, which primarily includes interactive data, professional knowledge bases, general knowledge bases, user databases and other electric customer service-related databases.

(2) Support layer. The support layer primarily provides AI capability support for the upper-level power customer service system, including two modules, an AI operation platform, and an AI basic platform.

(3) Service layer. The service layer combines the actual business requirements and business processes of the customer service center and builds an electric power intelligent customer service system based on the basic and operational capabilities of the AI layer.

(4) Application layer. The application layer builds applications based on the service and support layers, and provides external services through agent assistance, chat robots, business process guidance, intelligent outbound calls, etc., to achieve omni-channel access to the network and maximize the scope of customer service.

The intelligent customer service workflow is shown in Fig. 2. The user enters voice or text information through various access channels (email, phone, WeChat, Weibo, etc.). The system uses voice navigation, manual customer service, and intelligent Q&A on the unified call platform to conduct a reception. According to the business classification (query, complaint, suggestion) of the consultation, the system transfers the service request to the relevant business knowledge base and relevant business department. Depending on the specific scenario, a real-time reply is provided by the voice and intelligent Q&A, and a delayed reply is performed by a work order.

Let us use the voice channel as an example. After the system detects the user's voice input, it activates the voice recognition module and combines the professional vocabulary of electric power and user habits to convert the voice into text. The backend uses the language-understanding module to determine the user's appeal category based on the converted text and prompts the user on addressing related services in the form of voice broadcasts. Under the prompt of the system, the user will continue to prompt the required information using voice until the system collects all the required information and completes the business processing.

4 Semantic understanding model

As the aforementioned smart customer service application framework indicates, language understanding is not only the core of the entire intelligent customer service workflow, but also a key link in embodying the intelligence of the intelligent customer service dialogue system. It is the fundamental guarantee that the human–machine dialogue system can understand customer requirements similar to humans and manage business for customers [47]. Thus, it is necessary to improve the usability and intelligence of smart customer service to study the semantic understanding module of intelligent customer service.

Fig. 3 shows a language-understanding model based on the encoding and decoding framework of bidirectional recurrent neural networks [49-51], which consists of one input and two outputs. A BLSTM is used as the input sequence of the encoder E. Additionally, the encoded information is shared to the intent recognition and slot filling decoders. Subsequently, the attention mechanism is introduced to improve decode performance [14]. Finally, the results of the intent recognition and slot filling are obtained to realize the perception and understanding of user intent. In the model, the intent recognition decoder is composed of two stacked fully connected network (FCN) layers, where the input of the fully connected layer is the final output h_t of the coding layer, and the output is an intent vector whose size is the number of intent types. Here, a softmax function

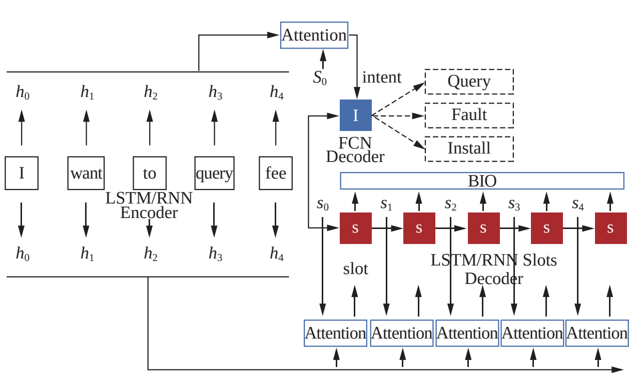

Fig. 3 Semantic understanding model with attention mechanism

is used to normalize intent vector. The slot filling decoder is composed of a single-layer LSTM with the same size as the encoding layer, whose input is the output h_t at the final moment t of the encode layer and the output is the slot information of each node.

In the intent decoding layer, all the hidden states $[h_1, h_2, \ldots, h_t]$ and target states s_0 of the encoding layer are directly calculated by the attention module to obtain a contextual semantic vector c_0 of the original input text. Subsequently, the vectors c_0 and s_0 are spliced together and activated through a fully connected layer to obtain the intent vector I. The entire calculation process is shown in Formula 1, where f_l is the fully connected layer, f_a is the attention module, and s_0 is the target state of the coding layer.

$$\vec{I} = f_l(f_a([h_1, h_2, ..., h_t], s_0) \oplus s_0) \tag{1}$$

In the slot decoding layer, for the output of each moment in the decoding layer, the hidden state of the previous moment is used as the hidden state of the LSTM unit at the current moment, and the hidden state calculated by the attention module with the encoding layer output is used as the input of the LSTM unit of the current moment.

The entire calculation process is shown in Formula 2, where f_l represents the fully connected layer, f_r represents the LSTM neuron at time j, f_a represents the attention module, and s_{i-1} represents the hidden state at the previous time in the decoding layer. For the state at each moment s_i, a fully connected layer activated by a rectified linear unit (ReLU) must be added to realize the slot classification mark.

$$s_i = f_l(f_r(f_a([h_1, h_2, ..., h_t], s_{i-1}), s_{i-1})) \tag{2}$$

As shown in Fig. 4, for the target state s_0, to obtain a global semantic vector representation, a 1-dimensional convolution kernel with a size of 2 and a step size of 2 is used to perform convolution on the text sequence and obtain the target state through maximum pooling across time steps.

The attention module accepts the hidden variables of the encoding layer at all moments, calculates these variables with a target variable S_j to obtain the attention weight w_j of each hidden variable, weights and sums the hidden layer variables of the coding layer according to these weights, and finally obtains the original context vector c_j of the input information.

$$a_i = h_i w s_j \tag{3}$$

$$w_i = \frac{e^{a_i}}{\sum_k e^{a_k}} \tag{4}$$

$$c_j = \sum_i w_i h_i \tag{5}$$

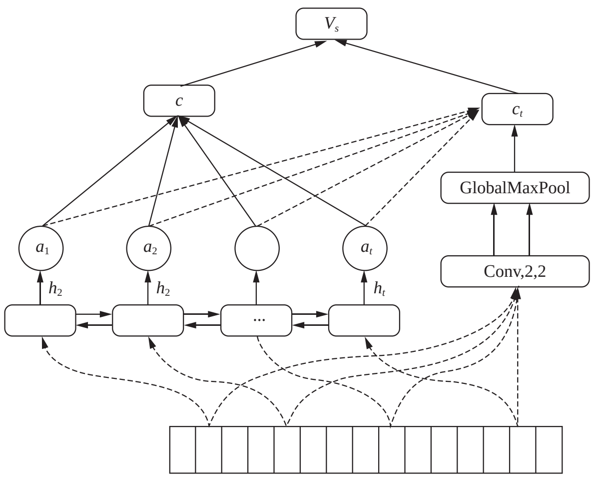

Fig. 4 Semantic representation of S_0 based on CNN improved attention mechanism

where $h_i \in R^n$ is the hidden state of the coding layer; $s_j \in R^n$ is the hidden state of the decoding layer at the previous moment; $w \in R^{n \times n}$ is the weight matrix that measures the correlation between the hidden state h_i of the coding layer and the target state s_j; $a_i \in R^n$ is the evaluation value of the importance of each hidden state relative to the hidden state of the current decoding layer after calculation. To facilitate subsequent calculations, it must be normalized using the softmax activation function to obtain the normalized weight $w_i \in R^n$; $c_j \in R^n$ is the final calculated context vector.

The overall workflow of the semantic understanding model used by an electric power intelligent customer service is shown in Fig. 5. The left side is the intent recognition module, which obtains the fixed-length vector representation of the entire text sequence through the attention module; the right side is the slot filling module, which uses attention. The module generates a corresponding fixed-length vector representation for each moment (word) and converts the fixed-length vector into a slot label probability distribution through a fully connected classifier. The cross-entropy loss function of intent recognition and slot filling is weighted and spliced to calculate the loss of the entire model, and the model is optimized using a gradient descent. The word

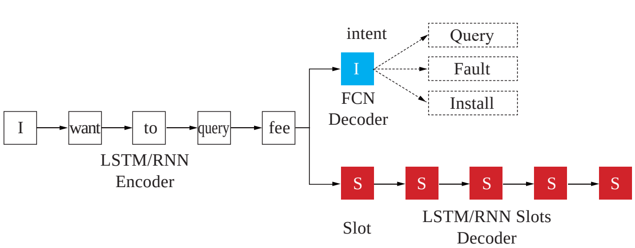

Fig. 5 Semantic understanding model without attention mechanism

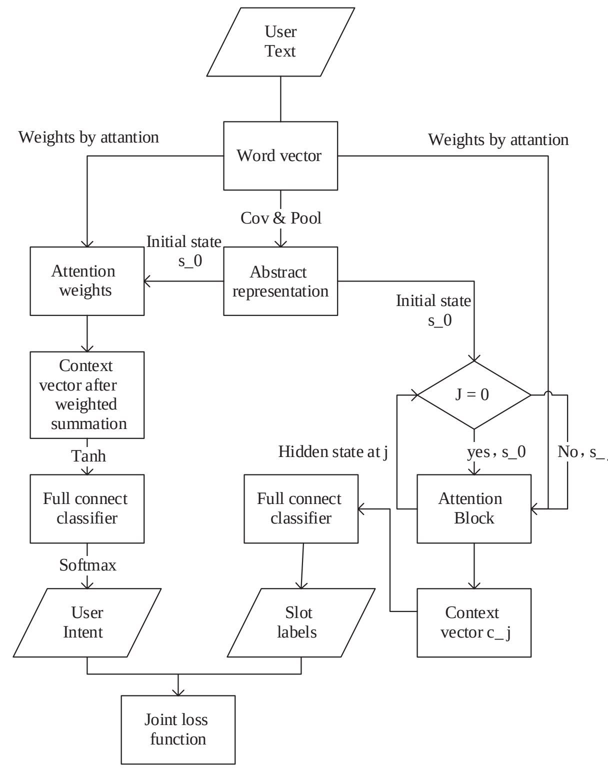

Fig. 6 Semantic understanding model workflow

vector in this model is affected by the two tasks of intent recognition and slot filling simultaneously. Thus, the key information of the two tasks is implicitly shared, and the accuracy of semantic understanding is increased.

5 Experiment and analysis

The experimental environment of this study is shown in Table 1, and it was evaluated on a Chinese conversation text dataset of electric power customer service. The Chinese dialog text dataset of an electric power customer service related to the field of electricity bills in a customer service center; all the data were recorded by telephone.

Table 1 Configuration of channels in experimental environment

Environment	Arguments
CPU/Memory	Intel Core i9-9820X / 32 GB DDR4
GPU	RTX 2080 Ti
OS/Deep Learning Framework	Ubuntu 18.04 / Keras 2.3

The entire Chinese dataset has 3260 pieces of data, 80% of which are training datasets, and 20% are test datasets. As shown in Table 2, there are 10 intents and 13 different slot labels. We used the BIO method to mark Chinese text, including 13 different slot labels. User-related content includes username, user account, mobile phone number and ID number. Equipment related includes equipment name, equipment type, equipment color, equipment status, location, date time, organization, and quantity.

Table 2 Chinese conversation text dataset of a power customer service

Intent #number	Example
Electricity fee inquiry #820	I want to check the electricity usage in December 2019
Electricity fee consultation #300	I want to inquire about the electricity price of my house
Electric meter query #260	I want to check the number of copies of my home
Abnormal battery query #380	The best battery usage in my home is abnormal
Inconsistent amount query #300	Why is my electricity purchase amount different from the actual amount?
Repeat payment query #240	How to deduct the electricity bill twice
Notice of Cancellation of Electricity Bill #120	I want to cancel the notification information of the electricity bill
Not received electricity bill inquiry #80	I want to ask why I did not receive the electricity bill
Power outage query #720	My home is out of power, please help me check the reason for the power outage
Business hall query #40	I want to inquire about the location of the nearby business hall

This study first used joint modeling to construct a codec language-understanding model M_1 without an attention mechanism (Fig. 6) as a reference benchmark. Subsequently, the attention mechanism was introduced in the decoding stage, and a language-understanding model M_2 based on the attention mechanism was obtained (Fig. 3). Next, in the initial stage of attention decoding of model M_2, the CNN structure shown in Fig. 4 was introduced to improve the effect of the initial semantic representation and obtain the language-understanding model M_3. Finally, the three models were tested on the dataset.

For the task of intent recognition, accuracy was used as the evaluation index. For the slot filling task, owing to the large gap in the number of tags, the accuracy rate was simply used as the evaluation index, and the low-frequency tags were ignored by the model. Therefore, the F1 score was used as the evaluation index to obtain a more credible model performance evaluation.

$$precison = \frac{TP}{TP + FP} \tag{6}$$

$$recall = \frac{TP}{TP + FN} \tag{7}$$

$$\mathrm{F1} = 2 \cdot \frac{precison \times recall}{precision + recall} \tag{8}$$

In these equations, TP represents the number of positive samples predicted to be positive by the model, FP represents the number of negative samples predicted to be positive by the model, FN represents the number of positive samples predicted to be negative by the model, and precision represents the actual number of samples predicted to be positive. The probability of a positive sample, recall represents the probability of being predicted as a positive sample in the actual positive sample.

Table 3 Performance of different models under the Seq2Seq framework

Model	Chinese Dataset	
	F1 (Slot)	Accuracy (Intent)
M1	86.8	88.9
M2	93.7	95.3
M3	94.1	95.7

Table 3 shows the accuracy of different models on the Chinese dataset. The F1 values of M_1, M_2, and M_3 reached 86.8%, 93.7%, and 94.1%, respectively, and the accuracy values reached 88.9%, 95.3%, and 95.7%, respectively. Experiments have demonstrated that, compared with the traditional encoding and decoding models, the introduction of the attention mechanism can effectively improve the performance of a model in intent recognition and slot positioning. Additionally, the attention mechanism can be optimized through a CNN module, which can also further improve the intent recognition to a certain extent. The accuracy rate effectively improves the performance of the language-understanding module.

Table 4 Comparison of accuracy based on ATIS (compared with models in other papers)

Model	Accuracy (Intent)	F1 (Slot)
TriCRF [52]	93.07%	94.42%
CNN TriCRF [53]	94.09%	95.42%
Attention BiRNN [54]	94.40%	95.78%
Our model (M3)	94.87%	96.49%

Moreover, based on the ATIS dataset, we compared model M_3 with some others. As shown in Table 4, model M_3 proposed in this paper achieved the best performance in accuracy and F1 (94.87% and 96.49%, respectively).

Table 5 System performance in 2020

Intent #number	Service time	System recall
Origin system	30.25 s	86.48%
With optimized model	26.11 s	90.47%

With the application of this language-understanding model, as of September 2020, as shown in Table 5, the average service time of intelligent customer service robots has been reduced from 30.25 to 26.11 s, the recall rate has increased from 86.48% to 90.47%, and customer service satisfaction has increased significantly. It significantly reduces the work pressure of customer service specialists and reduces the operating costs of the customer service center.

6 Conclusion

This paper first introduces key technologies such as machine learning, speech recognition, speech synthesis, language understanding, and knowledge graphs in the intelligent customer service system. Subsequently, it discusses the application framework and workflow of electric power intelligent customer service. Using language understanding as a breakthrough point, we conducted model research and analysis, proposed a language-understanding model based on the fusion of a CNN and attention, and applied this model to an electric power intelligent customer service system. The experimental results and application effects indicated that the language-understanding model that combines a CNN and an attention mechanism can better complete the language-understanding task, more accurately understand a user's intention, and significantly improve the intelligence and usability of the intelligent customer service system.

The intelligent customer service system is a combination of traditional customer service technology, experience and advanced AI technology, and has the characteristics of intelligence, mobility, social interaction, and the use of the cloud. It both has the functions of the traditional customer service system and can adequately solve the problems that traditional customer service have difficulty solving, and it can provide a better user experience for customers. In the future, with the continuous in-depth analysis and research on the application of intelligent customer service, intelligent customer service technology will eventually result in a new revolution to the customer service industry in terms of active support, personalized service, and high-reliability support.

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Declaration of Competing Interest

We declare that we have no conflict of interest.

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