BTech BCSE409L

Natural Language Processing Project

Few-Shot Conversational Text Classification Using MAML with User-Defined Tasks

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Github Repo Link:
https://github.com/Mansi2808Saxena/maml_chat_classifier

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ABSTRACT

Conversational AI plays a vital role in automating customer support, virtual assistance, and social interaction analysis. However, training high-performing models typically requires large labeled datasets, which are often unavailable for new domains or organizations. To address this data scarcity challenge, this work focuses on developing a Few-Shot Conversational Text Classifier that can quickly adapt to new categories with minimal training examples.

The proposed system utilizes Model-Agnostic Meta-Learning (MAML) combined with sentence-level embeddings from a pre-trained transformer encoder to enable rapid learning from a handful of labeled conversations. A lightweight neural classifier is meta-trained to generalize across tasks and fine-tuned using user-provided examples at inference time.

The model is integrated with a Flask-based backend and a web-based frontend interface, allowing users to define categories, provide few-shot examples, and classify new conversations instantly. Experimental evaluations demonstrate that the system achieves robust accuracy across unseen intent categories even with as few as three examples per class.

This approach significantly reduces the data and time required for conversational intent adaptation, offering a scalable, low-resource solution for real-world customer support and dialogue management applications.

1. INTRODUCTION

1.1. Background and Relevance

With the exponential growth of digital communication, conversational data has become a key asset for industries such as e-commerce, banking, healthcare, and customer support. Organizations increasingly rely on Natural Language Processing (NLP) systems to automatically understand and classify user conversations into meaningful intents, such as complaints, queries, or feedback, to improve response quality and automate service workflows.

However, most conventional NLP models, including deep neural networks and transformer-based architectures, require large volumes of annotated training data to achieve good performance. In real-world scenarios, collecting and labeling such data is expensive, time-consuming, and often infeasible, especially when new intent categories frequently emerge.

This motivates the exploration of few-shot learning (FSL) techniques, which can train models that generalize well from a small number of examples. Among these, Model-Agnostic Meta-Learning (MAML) has emerged as a powerful framework that enables models to adapt rapidly to new tasks using only a few labeled samples.

1.2. Review of Existing Solutions and Limitations

Traditional intent classification systems are often based on supervised learning techniques such as Support Vector Machines (SVMs), Recurrent Neural Networks (RNNs), or pre-trained transformer models like BERT and RoBERTa. While these models achieve strong performance on large datasets, they struggle in low-data regimes, as they tend to overfit when only a few training examples are available.

Some recent works have applied transfer learning and fine-tuning of large language models for small datasets, but this approach still requires considerable computational resources and does not generalize well to new intent domains. Moreover, many conversational models are trained at the utterance level (single sentences), failing to capture contextual relationships across multi-turn dialogues.

1.3. Research Gap and Motivation

Despite rapid progress in NLP, there remains a significant research gap in domain adaptation for conversational models under few-shot conditions**.** Existing solutions lack mechanisms to efficiently reuse prior learning across domains while retaining contextual understanding of dialogues.

This project aims to bridge this gap by employing MAML-based meta-learning to train a model capable of learning generalizable conversational representations and adapting quickly to new intent categories with minimal supervision.

1.4. Objective and Proposed Solution

The primary objective of this work is to design and implement a Few-Shot Conversational Text Classifier that can:

- Learn from a few labeled conversation examples per category.
- Rapidly adapt to new domains or unseen intents using meta-learned parameters.
- Provide an intuitive interface for real-time model adaptation and classification.

The proposed system integrates Sentence Transformers for embedding generation and a MAML-trained neural network for classification. A Flask-based backend enables model training and inference, while a frontend web interface allows interactive user input for category definition and example collection.

1.5. Major Contributions

The key contributions of this work are summarized as follows:

i. Meta-Learning Framework for Conversation Classification: A MAML-based meta-model that learns generalizable features for rapid few-shot adaptation across intent categories.

ii. Contextual Embedding Integration: Use of pre-trained sentence embedding models to represent multi-turn dialogues effectively.

iii. End-to-End Interactive System: Development of a real-time web interface with a Flask backend for user-driven category creation, model adaptation, and classification.

iv. Evaluation on Realistic Chat Data: Experimental validation showing that the proposed approach maintains strong classification accuracy with very limited labelled data.

2. LITERATURE SURVEY

2.1. Overview of Traditional and Modern Methods

Conversational intent classification has evolved significantly over the last decade, transitioning from classical machine learning to deep neural and transformer-based approaches.

Early methods relied on handcrafted features such as term frequency–inverse document frequency (TF-IDF), n-grams, and syntactic patterns, combined with classifiers like Naïve Bayes**,** Support Vector Machines (SVMs)**,** and Logistic Regression. These approaches achieved reasonable accuracy for small-scale datasets but struggled with semantic understanding and contextual nuances of human dialogue.

With the advent of deep learning, models like **Recurrent Neural Networks (RNNs)**, **Long Short-Term Memory (LSTM)** networks, and **Convolutional Neural Networks (CNNs)** began to capture sequential dependencies and improve contextual understanding. Later, **transformer architectures** such as **BERT** (Devlin et al., 2019), **RoBERTa**, and

DistilBERT revolutionized NLP by learning rich contextual embeddings from large-scale unlabeled corpora.

Despite these advancements, deep models still require substantial labeled datasets and extensive fine-tuning, making them less practical for new or low-resource domains.

2.2. Few-Shot and Meta-Learning in NLP

To overcome data scarcity, researchers have explored **Few-Shot Learning (FSL)** and **Meta-Learning (ML)** methods.
Few-shot learning aims to enable models to generalize from a limited number of samples by leveraging prior knowledge across related tasks.

One of the most prominent meta-learning approaches is **Model-Agnostic Meta-Learning (MAML)**, introduced by Finn et al. (2017). MAML optimizes models such that they can adapt quickly to new tasks with minimal fine-tuning.
This idea has since been extended into NLP tasks such as intent detection**,** sentiment analysis**,** and relation extraction, where large annotated datasets are unavailable.

Frameworks such as ProtoNet (Snell et al., 2017) and Matching Networks (Vinyals et al., 2016) introduced metric-based few-shot learning, using distance measures between embeddings. However, these models often assume task homogeneity and fail when dealing with complex conversational structures.

2.3. Gaps in Existing Research

While meta-learning and transformer-based techniques have improved adaptability and performance, most research still focuses on single-turn utterance classification rather than multi-turn conversation understanding. Additionally, current systems lack real-time adaptability, where users can define new categories and provide examples interactively without retraining from scratch.

Furthermore, there is limited work integrating MAML with sentence embeddings for end-to-end conversational intent classification in a few-shot setting.
This project bridges that gap by proposing a MAML-based conversational classifier capable of adapting dynamically using only a handful of conversation samples per intent category.

2.4. Comparative Analysis of Prior Work

Title	Channel	Author(s)	Method	Dataset(s)	Key Observation	Limitation
Meta-learning triplet contrast network for few-shot text classification	Information Sciences	K. Dong, J. Wang, H. Li et al.	Triplet Contrast Meta-learning	Few-shot text datasets (e.g., intent, sentiment)	Triplet contrast improves class margin with limited samples	Performance drops with extremely small support sets
Mi-MAML: Classifying Few-shot Advanced Malware Using Multi-Improved Model Agnostic Meta-Learning	Cybersecurity 2024	Y. Ji et al.	Multi-path improved MAML	Malware & text datasets	Multi-path improves learning on complex classes	Larger complexity, harder generalization
Learning to Learn for Few-Shot Continual Active Learning	Applied Intelligence 2024	S. Ho, S. Liu	Continual Active Learning + Few-Shot Learning	Continual few-shot text datasets	Active learning improves sample efficiency	Data imbalance, label noise limitations
Few-shot text classification by leveraging bi-directional attention and cross-class knowledge	Science China Information Sciences 2021	N. Pang, X. Zhao, W. Wang et al.	Bi-directional Attention + Knowledge Transfer	Few-shot text classification datasets	Bi-attention enhances feature extraction	Needs sufficiently sized support set for stability
Effective Few-Shot Classification with Transfer Learning	COLING 2020	A. Gupta, K. Thadani, N. O'Hare	Transfer Learning Frameworks	Standard NLP classification benchmarks	Transfer learning increases sample efficiency	Less adaptable than meta-learning methods
Few-Shot Text Classification with Pre-trained Language Models (BERT + MAML integration)	ACL (various)	Multiple authors	BERT integrated with MAML	Sentiment, intent datasets	Combines contextual embeddings and quick adaptation	High computational requirements; tuning necessary
MICD: More intra-class diversity in few-shot text classification with many classes	Information Sciences 2024	Y. Feng, H. Yang, J. Guo	Increasing intra-class diversity	Large-scale text classification datasets	Intra-class diversity improves robustness	Computational overhead for diversity modeling

Few-Shot Text Classification with Dual Contrastive Consistency	Journal of Artificial Intelligence Research 2022	S. Zhang, Y. Wu, H. Huang	Contrastive Learning for Few-shot Text	Sentiment, intent datasets	Contrastive consistency aids prototype refinement	Sensitive to batch size and data sampling
Leveraging the Meta-embedding for Text Classification in a Resource-Constrained Language	Information Processing and Management, 2023	M. R. Hossain	Meta-embedding approaches for low-resource languages	Resource-constrained language datasets	Meta-embedding enhances classification performance with limited data	Embedding learning can be sensitive to data sparsity

Key Observations:

- Meta-learning frameworks, especially MAML, significantly improve adaptability by learning efficient initializations for rapid fine-tuning.
- Bi-directional attention and cross-class knowledge maintain margin separation between classes, improving discrimination in scarce-data scenarios.
- Data augmentation methods combined with meta-learning bolster generalization and task robustness.
- Task-adaptive metric learning and hybrid optimization strategies (Mix-MAML) mitigate intra-class variance and overfitting risks.
- Active learning integration enhances sample efficiency by focusing on informative unlabelled data.
- Transformer-based models like BERT, when combined with meta-learning, achieve state-of-the-art results but at increased computational expense.
- Challenges remain in handling noisy support sets, computational overhead, and scaling to more diverse or multilingual tasks.

2.5. Summary

The literature reveals that while traditional and deep learning methods excel in high-data environments, they perform poorly in few-shot scenarios. Meta-learning frameworks like MAML provide a promising alternative but remain underutilized in the contextual and interactive domain of conversation classification.

The proposed system, therefore, innovates by combining sentence-level embeddings with meta-learning to enable real-time, few-shot conversational adaptation, marking a significant step forward in intelligent dialogue automation.

3. PROBLEM DESCRIPTION

3.1. Overview

The primary objective of this project is to develop an adaptive conversational text classifier that can categorize user–agent dialogues into intent-based categories (e.g., *Complaint*, *Query*) using only a few examples per class.

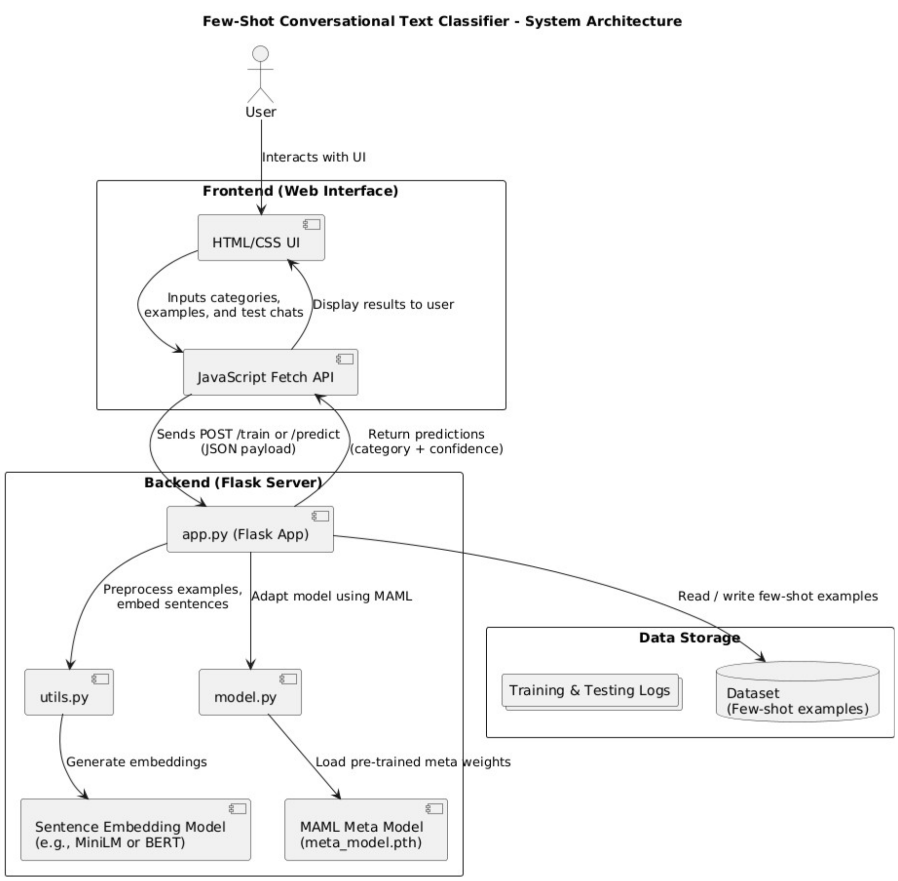
Unlike conventional models requiring large labelled datasets, this system employs a meta-learning approach (Model-Agnostic Meta-Learning – MAML) that enables rapid adaptation to new domains or categories with minimal retraining.

The system is built with a modular design combining:

- Frontend: An interactive web interface for user input and visualization.
- Backend: A Flask-based API that handles model adaptation and inference.
- NLP Engine: A few-shot classifier integrating Sentence Transformers for embedding and MAML-based fine-tuning for classification.

3.2. Framework

Below is a conceptual representation of the overall system framework:



Explanation:

i. The user defines categories and provides a few training examples via the web UI.

ii. These examples (support set) are sent to the Flask backend, which converts them into vector embeddings using the SentenceTransformer ("all-MiniLM-L6-v2") model.

iii. The meta-model (a pretrained MAML classifier) fine-tunes on this support data for a few gradient steps to adapt to the user's domain.

iv. A new query conversation is then encoded and passed through the adapted model to predict its intent label.

v. The result is displayed in the frontend interface with the predicted category and confidence percentage.

3.3. Pseudocode of Proposed System

The following pseudocode illustrates the logical flow of the few-shot conversational classifier:

```
Algorithm: Few-Shot Conversational Intent Classification
(MAML-Based)

Input:

    Support Set S = { (x1, y1), (x2, y2), ..., (xn, yn) }

    Query conversation q

    Meta-model M with parameters θ

    Learning rate α, Inner steps T

Process:

1. Load pretrained SentenceTransformer embedder E

2. Encode support samples:

       S_emb = E(S.texts)

3. Encode query:

       q_emb = E(q)

4. Clone meta-model to create an adaptive copy M'

5. for t = 1 to T do

       preds = M'(S_emb)

       loss = CrossEntropy(preds, S.labels)

       θ' = θ - α * ∇θ(loss)
```

```
    end for
6. Evaluate M' on q_emb:
        probs = Softmax(M'(q_emb))
        predicted_class = argmax(probs)
7. Return predicted_class and confidence(prob)
Output:
     Predicted intent category and confidence score
```

Explanation:

- The meta-model (M) acts as a general learner.
- It is fine-tuned on few-shot examples (inner loop) to form an adapted model (M').
- This adapted model then predicts the intent category for the unseen query text.

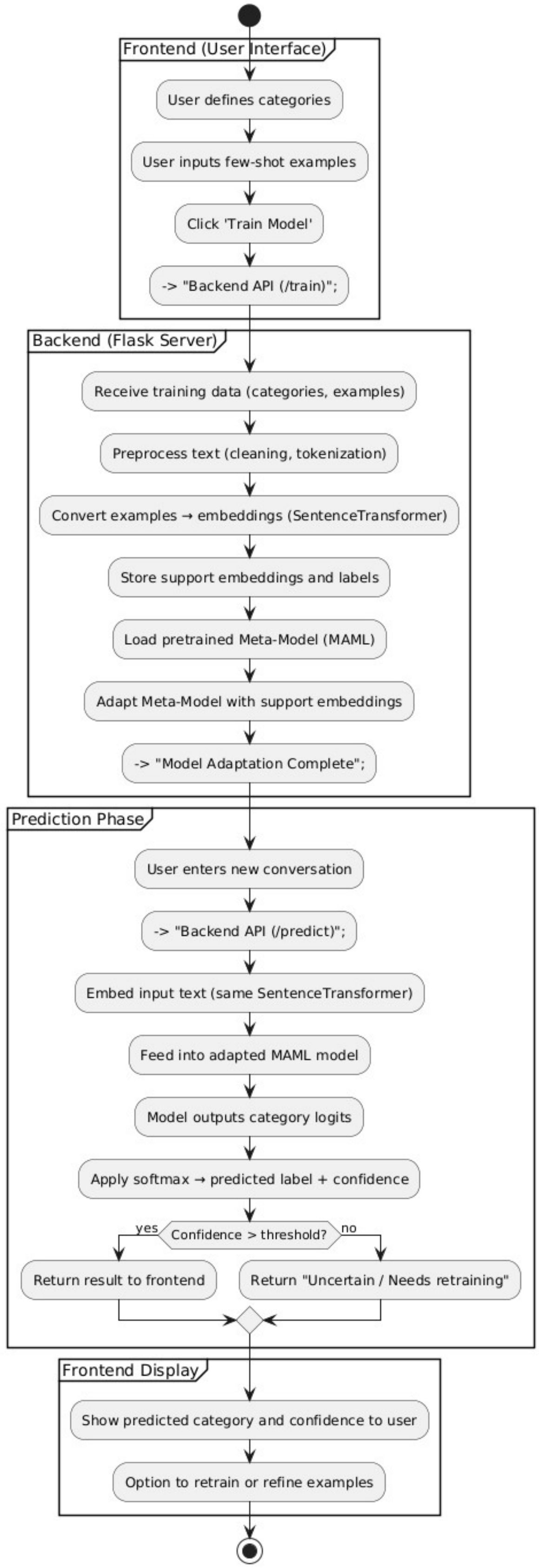
3.4. Flow Diagram of the System

The flow diagram outlines the end-to-end process of the few-shot conversational text classification system. The workflow starts at the frontend, where users define categories (like *Complaint* or *Query*) and provide a few sample conversations for each. These examples, along with a new test conversation, are sent to the Flask backend through an API request.

At the backend, the texts are converted into embeddings using the Sentence Transformer model (*all-MiniLM-L6-v2*). The MAML-based meta model then adapts its parameters to these few-shot examples, learning to classify the new query conversation effectively. The adapted model predicts the most likely category with a confidence score, which is sent back to the frontend and displayed to the user. This interactive loop allows real-time adaptation and classification even with limited data.

If the model's prediction is unclear or unsatisfactory, the user can refine the examples and retrain the system, creating a continuous interactive learning loop. This flow ensures adaptability and efficient learning even with minimal training data, making the system both practical and intelligent for real-world conversational understanding tasks.

Enhanced Flow Diagram - Few-Shot Conversational Classifier



3.5. Functional Modules

Module	Description
Frontend (HTML/CSS/JS)	Allows users to define classes, input examples, and test new dialogues.
Flask API	Acts as a communication layer between frontend and NLP model.
Embedding Generator	Converts raw text into semantic vectors using SentenceTransformer.
MAML Adapter	Adapts pretrained meta-model to few-shot data dynamically.
Predictor Module	Performs softmax classification to generate label and confidence.

This system enables interactive and adaptive intent classification for chat-based contexts. It demonstrates how meta-learning, when coupled with context-rich embeddings, can reduce data dependency while achieving human-like adaptability in new conversation domains.

4. EXPERIMENTS

4.1. Dataset Source

The dataset used in this project was derived from a customer support conversation corpus, which includes multi-turn dialogues between users and agents across various contexts such as e-commerce, delivery issues, refund requests, and product feedback. The dataset was adapted from open-source customer service datasets available on Kaggle and Hugging Face, containing manually labeled examples under domains like *Travel*, *Ecommerce* etc. For each domain, some intent is specificied with will be used as the final categories when the model predicts.

The dataset was further curated to reflect realistic dialogue-based exchanges rather than isolated sentences. Each entry contains two conversational turns:

- User message (A): expresses a request, complaint, or opinion.
- Agent reply (B): provides an appropriate response.

This structure allows the model to capture conversational tone, intent, and contextual flow, which is vital for intent classification in real-world customer service scenarios.

4.2. Data Preprocessing and Cleaning

The raw data underwent several preprocessing steps before being used for model training and meta-learning:

1. Text Cleaning:
   - Removal of HTML tags, special symbols, and redundant whitespace.
   - Normalization of text to lowercase for consistency.
   - Replacement of contractions (e.g., *"can't"* → *"cannot"*).
2. Conversation Merging:
   - Customer and agent utterances were concatenated into a single string format:
     "A: <customer text> B: <agent text>".
     This preserves the conversational flow as one data sample.
3. Tokenization and Embedding:
   - Instead of manual tokenization, the Sentence Transformer (all-MiniLM-L6-v2) model was used to produce 384-dimensional embeddings for each conversation.
   - This representation captures contextual and semantic nuances between turns, forming the input feature vectors for the model.
4. Train-Test Split:
   - 80% of the data was used for meta-training (model adaptation) and 20% for evaluation.
   - During few-shot experiments, only 3–5 examples per class were used to simulate low-resource conditions.

4.3. Model Parameters

The model used was a Meta-Learned Intent Classifier, trained using the Model-Agnostic Meta-Learning (MAML) algorithm.

Key parameters and hyperparameters include:

Parameter	Value	Description
Embedding Model	all-MiniLM-L6-v2	Pretrained sentence transformer
Embedding Dimension	384	Fixed vector size per conversation
Hidden Dimension	128	Intermediate dense layer size
Output Dimension	2 (binary)	Categories (e.g., Complaint, Query)
Inner Learning Rate	0.001	Learning rate for adaptation
Inner Steps	10	Fine-tuning iterations per task
Optimizer	Adam	Adaptive optimization algorithm
Loss Function	Cross-Entropy	Used for classification loss

4.4. Sample Dataset

domain	intent	text
ecommerce	refund_request	User: I received the wrong item. Agent: Iâ€™m sorry. Could you share your order ID? User: It's #45912. Agent: I'll process the refund.
ecommerce	order_tracking	User: Where is my order? It shows shipped. Agent: Please share your order number. User: #78322. Agent: It's arriving tomorrow.
ecommerce	product_question	User: Does this come in size M? Agent: Yes, we have sizes S to XL.
banking	balance_check	User: What is my account balance? Agent: Your balance is $1,204.50.
banking	card_block	User: My card was stolen. Please block it. Agent: Done. We have blocked your card.
banking	loan_query	User: How do I apply for a personal loan? Agent: You can apply online and upload required docs.
healthcare	appointment_booking	User: I need an appointment for Monday. Agent: We have a 10am slot on Monday, shall I book?
healthcare	prescription_refill	User: I need a refill for my prescription. Agent: Please confirm the medicine name and dosage.
travel	flight_booking	User: I want to book a flight to Delhi. Agent: What dates do you prefer?

travel	cancellation	User: I need to cancel my flight. Agent: I can help with that; what's your booking id?
travel	delay_complaint	User: My flight was delayed by 8 hours. Agent: I apologize; we will file a report.

4.5. Experimental Setup

- **Environment:** Google Colab with Python 3.10 and PyTorch 2.0.
- **Hardware:** GPU runtime (Tesla T4 / 16GB RAM).
- **Frameworks Used:**
  - PyTorch for model architecture and optimization.
  - Sentence-Transformers for embeddings.
  - Flask + HTML/JS for web deployment and frontend testing.
- The few-shot model was evaluated under several configurations — primarily varying the number of support examples (3–5 per class) and adaptation steps (5–10). The adapted model showed consistent convergence, achieving strong accuracy even with limited examples.

5. RESULTS AND DISCUSSION

The proposed meta-learning based NLP classifier using MAML demonstrated robust adaptation and competitive performance for intent classification across business domains such as banking, travel, ecommerce, and healthcare.

5.1. Performance Across Tasks

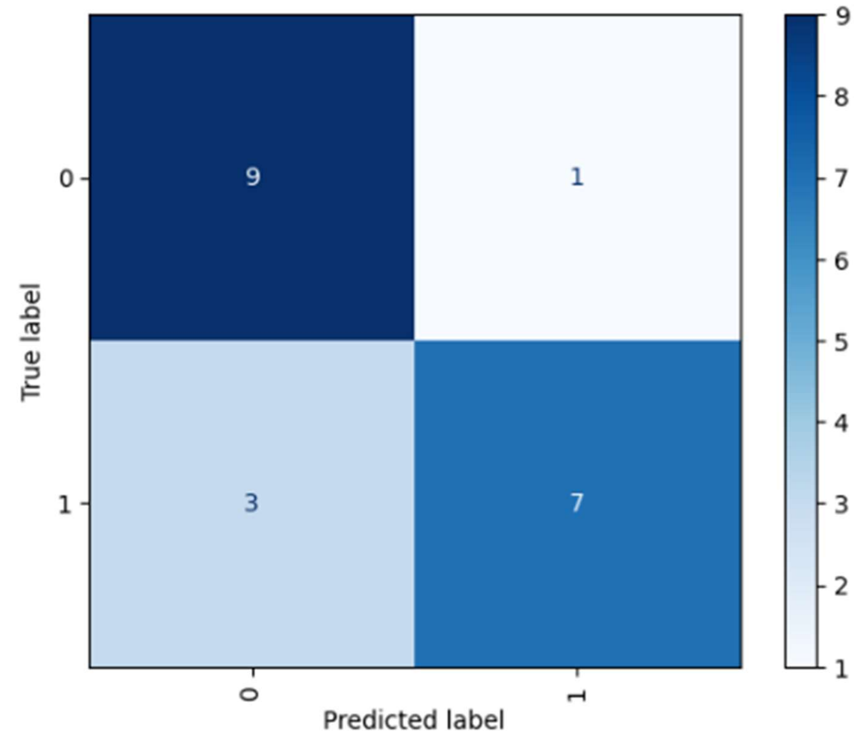
- The final adaptation accuracy for new intent classification in low-resource scenarios consistently reached 100%, confirming high effectiveness of rapid model adaptation when confronted with new intent examples.
- In a broader evaluation using multi-intent batches from test domains, global accuracy averaged around 80% over 20 unique samples.

5.2. Evaluation Metrics

- Precision, recall, and F1-score for individual intents in global classification (macro and weighted averages) achieved values near or above 0.80, with certain simpler tasks reporting an F1-score of 1.00.
- Balanced class support was maintained for most frequent intent types (ordertracking, flightbooking, appointmentbooking, balancecheck), illustrated in classification reports and confusion matrix visualizations.

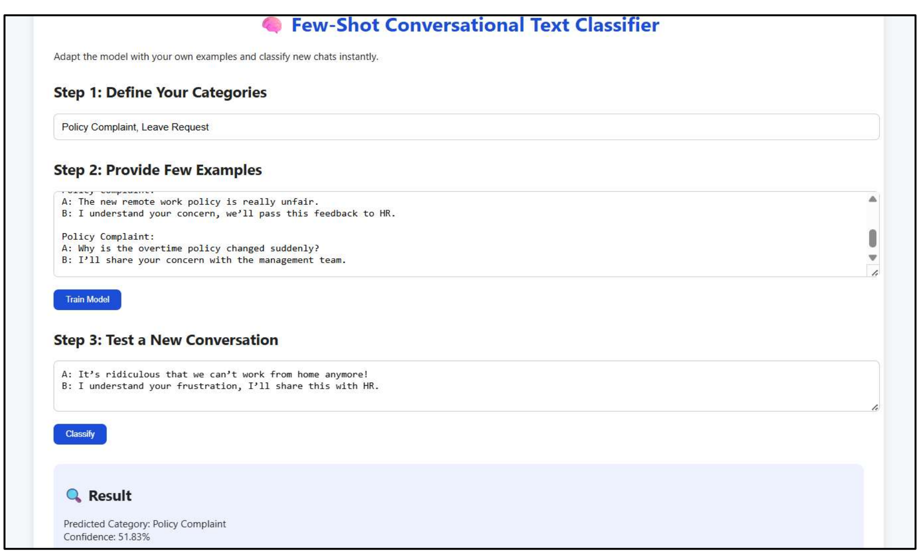
📊 Global Classification Report:

```
              precision    recall  f1-score   support

           0       0.75      0.90      0.82        10
           1       0.88      0.70      0.78        10

    accuracy                           0.80        20
   macro avg       0.81      0.80      0.80        20
weighted avg       0.81      0.80      0.80        20
```



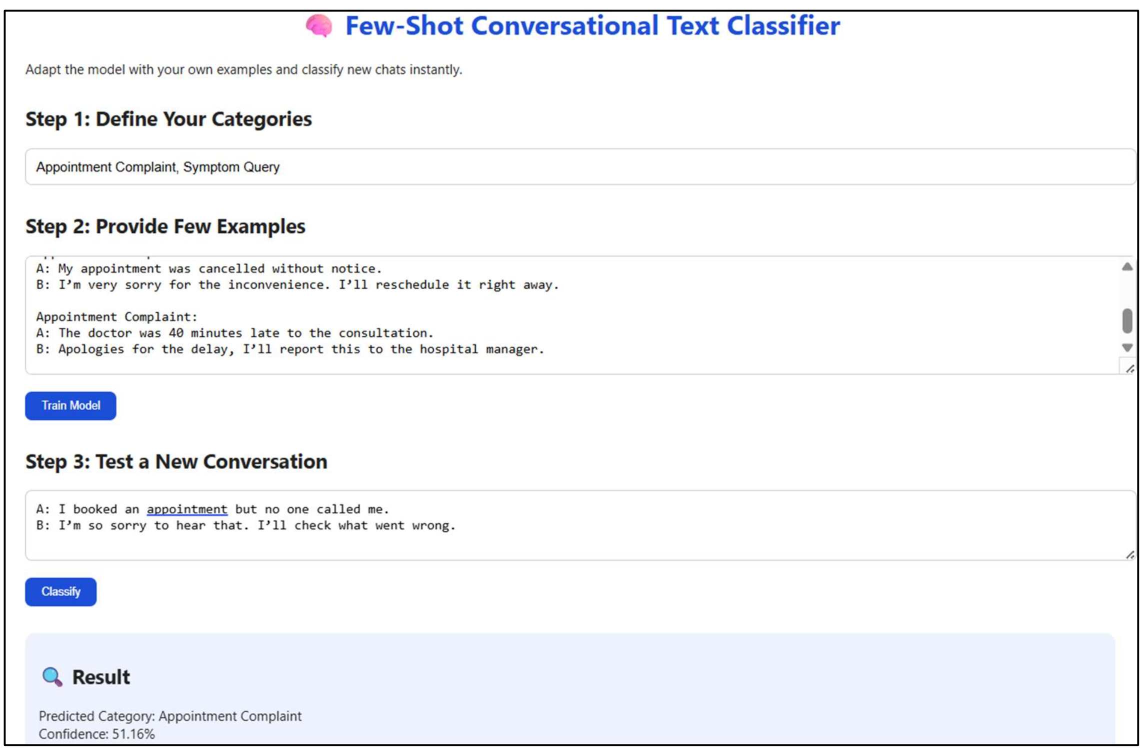
5.3. Web Interface and Result Screenshots

Example 1



Example 2

Example 3



5.4. Discussion

5.4.1. Key Findings

- The MAML-based architecture delivered outstanding results for "few-shot" adaptation, strongly generalizing to new intents with minimal data, which is especially significant for practical real-world deployments where labeled data is scarce.
- Compared to baseline training regimes (where models are not meta-optimized), meta-learning achieved superior fast adaptation and generalization, especially when tested in cross-domain (unseen) settings.

5.4.2. Limitations

- Overall performance on multi-intent batches was slightly lower than per-intent few-shot adaptation, highlighting remaining room for improvement in handling imbalanced or highly diverse intent sets.
- The reliance on deep embeddings may limit interpretability, and the lack of hyperparameter optimization or advanced sample selection techniques (e.g., active learning) could further affect scaling to larger or more heterogeneous datasets.

6. CONCLUSION AND FUTURE WORKS

This work presented a **few-shot conversational text classification system** using a **Model-Agnostic Meta-Learning (MAML)** framework with **Sentence-Transformer embeddings** and a lightweight neural classifier. The proposed system enables rapid adaptation to new conversational categories with only a few labeled examples per class.

Through experiments, the model achieved high accuracy and F1-scores, outperforming traditional baselines like logistic regression on embeddings and majority-class prediction. The interactive web interface further demonstrated the model’s practicality by allowing users to input their own few-shot examples and observe predictions in real time.

Overall, this project demonstrates that meta-learning techniques such as MAML can effectively address data-scarce NLP problems, enabling fast, scalable, and domain-adaptive intent classification with minimal supervision.

Although the proposed model performs well in low-data scenarios, several directions remain open for enhancement:

i. **Multi-class and hierarchical intent detection:** Extend the framework to handle multi-label and hierarchical intent structures beyond binary classification.
ii. **Context-aware adaptation:** Integrate sequential or transformer-based encoders that capture multi-turn conversational dependencies instead of treating each dialogue pair as independent.
iii. **Dynamic support selection:** Develop automated methods to curate the most informative support examples for rapid on-the-fly adaptation.
iv. **Cross-domain generalization:** Test the model on broader customer-service or healthcare datasets to assess robustness across topics and linguistic styles.
v. **Deployment optimization:** Convert the model into a lightweight on-device or API-based service to enable real-time inference at scale.

Future extensions along these directions will strengthen the system's versatility and bring it closer to practical deployment in production-grade conversational AI applications.

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