# Customer Query Classification System

## Technical Report - AI/ML Engineer Recruitment Task

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**Date:** July 2025  
**Task:** Automated Customer Query Classification

## Introduction

### Problem Statement

Customer support teams receive diverse queries daily, ranging from booking inquiries and baggage policies to payment issues and flight changes. Manual categorization of these queries is time-consuming and inconsistent. The objective is to develop an automated system that can accurately classify customer queries into predefined categories, enabling efficient routing to appropriate support teams.

### Approach Overview

I developed a comprehensive machine learning solution using a **predictive classification approach**. The solution leverages advanced text preprocessing, systematic model comparison, and focuses on production deployment considerations. Key principles followed:

* **Data-driven methodology:** Comprehensive EDA to understand query patterns
* **Systematic evaluation:** Comparison of multiple algorithms from simple to complex
* **Production-focused design:** Emphasis on interpretability, reliability, and scalability
* **Ethical AI considerations:** Bias detection, fairness assessment, and transparency

### Key Results Achieved

* **98.71% F1-Score** using optimized Logistic Regression
* **<100ms inference time** for real-time processing capability
* **1.27% error rate** with logically explainable misclassifications
* **Production-ready model** with comprehensive evaluation framework

## Methodology

### Data Understanding and Preprocessing

#### Dataset Characteristics

* **Training Set:** 20,000 labeled customer queries
* **Test Set:** 5,977 unlabeled queries for final evaluation
* **Categories:** 30 distinct customer service categories
* **Language:** English text data
* **Quality:** High-quality dataset with minimal missing values

#### Comprehensive Preprocessing Pipeline

**Text Cleaning Implementation:**

class TextPreprocessor:

def \_\_init\_\_(self):

self.stop\_words = set(stopwords.words('english'))

self.lemmatizer = WordNetLemmatizer()

# Domain-specific stop words for airline queries

airline\_stopwords = {'flight', 'flights', 'ryanair', 'airline', 'customer', 'service'}

self.stop\_words.update(airline\_stopwords)

def preprocess\_text(self, text, method='lemmatize'):

# Clean text: URLs, emails, special characters

cleaned\_text = self.clean\_text(text)

# Advanced tokenization with lemmatization

tokens = self.advanced\_tokenize(cleaned\_text)

return ' '.join(tokens)

**Feature Engineering:**

* **Text Statistics:** Character count, word count, sentence count
* **Punctuation Analysis:** Question marks, exclamation marks for urgency detection
* **Domain Keywords:** Airline-specific keyword presence detection
* **TF-IDF Vectorization:** Optimized parameters (10k features, (1,2)-grams)

### Model Choice: Predictive vs Generative

**Decision: Supervised Classification**

I chose a predictive classification approach over generative methods for several reasons:

1. **Labeled Data:** High-quality labeled dataset available for supervised learning
2. **Accuracy Requirements:** Need for high precision in production environment
3. **Interpretability:** Business needs explainable classification decisions
4. **Performance:** Real-time inference requirements favor efficient models
5. **Resource Efficiency:** Cost-effective deployment without specialized hardware

### Systematic Model Evaluation

#### Algorithm Comparison Results

| **Algorithm** | **F1-Score** | **Accuracy** | **Training Time** | **Assessment** |
| --- | --- | --- | --- | --- |
| **Logistic Regression (Tuned)** | **98.71%** | **98.71%** | 2.7s | 🏆 **Best** |
| SVM (RBF kernel) | 98.58% | 98.58% | 96.3s | Excellent |
| Random Forest | 98.42% | 98.42% | 8.5s | Very Good |
| XGBoost | 98.01% | 98.01% | 107.5s | Good |
| Ensemble Voting | 98.48% | 98.48% | 426.0s | Good but slow |
| Naive Bayes | 96.32% | 96.32% | 1.8s | Baseline |

**Key Finding:** Simple models with proper preprocessing can achieve excellent performance, often outperforming complex ensemble methods.

#### Hyperparameter Optimization

**Logistic Regression Tuning:**

* **Method:** RandomizedSearchCV
* **Best Parameters:** C=10.0, penalty='l2', solver='liblinear'
* **Improvement:** +0.13% F1-score over default parameters

#### Cross-Validation Analysis

**5-Fold Stratified CV Results:**

* **Logistic Regression:** 98.58% ± 0.13% (highly stable)
* **SVM:** 98.72% ± 0.20% (excellent but higher variance)
* **Consistent Performance:** All top models show <0.3% variance

## Results

### Model Performance Analysis

#### Overall Performance

* **Best Model:** Optimized Logistic Regression
* **F1-Score:** 98.71% (weighted average)
* **Accuracy:** 98.71%
* **Error Rate:** 1.27% (51 errors out of 4,000 validation samples)
* **Training Efficiency:** 2.7 seconds training time

#### Per-Category Performance

**Perfect Performance (100% F1-Score):**

* Business Travel, Duty-Free Shopping, Group Bookings, Travel Insurance

**Most Challenging Categories:**

* Frequent Flyer Miles: 96.3% (semantic overlap with Loyalty Programs)
* Flight Bookings: 96.9% (some overlap with Payment Issues)
* Loyalty Programs: 96.9% (similar terminology to Frequent Flyer)

#### Error Analysis

**Top Error Patterns:**

1. **Frequent Flyer Miles ↔ Loyalty Programs:** 5 cases (semantic similarity)
2. **Baggage Policies ↔ Lost and Found:** 3 cases (related concerns)
3. **Flight Bookings ↔ Payment Issues:** 3 cases (multi-intent queries)

**Key Insight:** All errors are logically explainable confusions between semantically similar categories, not random misclassifications.

### Production Testing Results

#### Real-World Validation

**Testing Dataset:** 999 customer queries from production environment

**Performance Metrics:**

* **Average Confidence:** 95.3% (excellent model certainty)
* **High Confidence (≥80%):** 96.1% of predictions
* **Medium Confidence (50-80%):** 3.7% of predictions
* **Low Confidence (<50%):** 0.2% of predictions

**Category Distribution:**

* **Most Common:** Promotions and Discounts (173 cases)
* **Top Categories:** Travel Vouchers, Travel Restrictions, Frequent Flyer Miles
* **Perfect Accuracy:** Travel voucher queries consistently 99.2% confidence

#### Confidence Analysis

**High Confidence Examples:**

Query: "apply travel voucher book"

✅ Predicted: Travel Vouchers

🎯 Confidence: 99.2%

**Review Required (Low Confidence):**

Query: "extra charge book"

❓ Predicted: Payment Issues (34% confidence)

🤔 Alternative: Flight Bookings (30.1%)

### Model Validation

#### Learning Curve Analysis

* **Overfitting Check:** Minimal train-validation gap (0.009)
* **Model Stability:** Low variance across CV folds (±0.13%)
* **Data Sufficiency:** Performance plateaus indicating adequate training data

#### Production Readiness Assessment

* **Deployment Status:** 🟢 **PRODUCTION READY**
* **Automation Strategy:** 96% of queries can be auto-routed
* **Human Review:** Only 4% require manual intervention
* **Recommended Threshold:** ≥85% confidence for automation

### Future Improvements

**Technical Enhancements:**

* **Active Learning:** Incorporate human feedback for continuous improvement
* **Advanced Models:** Explore transformer-based models (BERT fine-tuning)
* **Multi-label:** Handle queries with multiple intents
* **Feature Engineering:** Customer context and interaction history

**Operational Improvements:**

* **Confidence Threshold Optimization:** Based on production data
* **Real-time Learning:** Incremental model updates
* **Multilingual Support:** Expand to other European languages

## MLOps Integration

### Production Deployment Strategy

#### Proposed Architecture

Customer Query → API Endpoint → Text Processing → Model Inference → Category + Confidence

**Core Components:**

* **API Layer:** FastAPI for high-performance REST endpoints
* **Model Serving:** Joblib model loading with scikit-learn
* **Preprocessing:** Real-time text cleaning and vectorization
* **Response:** JSON with category, confidence score, and metadata

#### API Implementation Concept

from fastapi import FastAPI

from pydantic import BaseModel

class QueryRequest(BaseModel):

query: str

class QueryResponse(BaseModel):

category: str

confidence: float

@app.post("/classify")

async def classify\_query(request: QueryRequest):

# Preprocess query

processed\_text = preprocessor.preprocess\_text(request.query)

# Model prediction

prediction = model.predict([processed\_text])[0]

confidence = model.predict\_proba([processed\_text]).max()

# Return result

category = label\_encoder.inverse\_transform([prediction])[0]

return QueryResponse(category=category, confidence=float(confidence))

### Deployment Considerations

#### Infrastructure Requirements

* **Compute:** Minimal requirements - standard CPU sufficient
* **Memory:** ~2GB for model artifacts and preprocessing
* **Storage:** Model files, logs, and temporary processing
* **Network:** Standard HTTP/HTTPS for API endpoints

#### Scalability Planning

* **Horizontal Scaling:** Multiple API instances behind load balancer
* **Caching:** Model artifacts cached in memory for faster inference
* **Monitoring:** Response time, accuracy, and error rate tracking
* **Health Checks:** Endpoint availability and model performance validation

### Model Lifecycle Management

#### Version Control Strategy

* **Model Versioning:** Semantic versioning for model releases
* **Artifact Storage:** Centralized storage for model files and metadata
* **Rollback Capability:** Previous model versions for emergency rollback
* **Performance Tracking:** Historical performance metrics

#### Continuous Improvement

* **Performance Monitoring:** Track accuracy degradation over time
* **Data Drift Detection:** Monitor input text distribution changes
* **Feedback Collection:** Gather corrections from human agents
* **Retraining Schedule:** Regular model updates with new data

### Monitoring and Maintenance

#### Key Metrics to Track

* **Model Performance:** Accuracy, F1-score, confidence distribution
* **System Performance:** Response latency, throughput, error rates
* **Business Metrics:** Automation rate, human intervention frequency

#### Alert Configuration

* **Performance Degradation:** Accuracy drops below threshold
* **System Issues:** High error rates or slow response times
* **Data Quality:** Unusual patterns in incoming queries

## Ethical Considerations

### Bias Detection and Assessment

#### Potential Bias Sources

**Language Complexity Bias:**

* **Risk:** Queries with poor grammar or spelling might be misclassified
* **Assessment:** Analyze performance across different language proficiency levels
* **Mitigation:** Include diverse writing styles in training data

**Category Representation Bias:**

* **Current Status:** Relatively balanced dataset (max/min ratio: 2.18:1)
* **Risk:** Some categories might be systematically favored
* **Mitigation:** Monitor per-category performance and adjust thresholds

**Geographic/Cultural Bias:**

* **Risk:** Different regional expressions might be misunderstood
* **Assessment:** Would require geographic metadata for thorough analysis
* **Mitigation:** Diverse training data collection across regions

#### Fairness Assessment Framework

def assess\_model\_fairness(model, test\_data, protected\_attribute):

"""

Basic fairness assessment across different groups

"""

groups = test\_data[protected\_attribute].unique()

performance\_by\_group = {}

for group in groups:

group\_data = test\_data[test\_data[protected\_attribute] == group]

accuracy = model.score(group\_data['text'], group\_data['label'])

performance\_by\_group[group] = accuracy

# Calculate fairness metrics

max\_diff = max(performance\_by\_group.values()) - min(performance\_by\_group.values())

return performance\_by\_group, max\_diff

### Privacy and Data Protection

#### Data Handling Principles

**Data Minimization:**

* Only query text processed, no personal identifiers stored
* Temporary processing with automatic cleanup
* Model training on anonymized historical data

**Processing Transparency:**

* Clear documentation of data usage
* Customer awareness of automated classification
* Option for human review of AI decisions

#### Privacy-Preserving Design

**Technical Measures:**

* **Stateless Processing:** No customer data persistence
* **Anonymization:** Remove any potential identifying information
* **Secure Processing:** Encrypted data transmission
* **Access Control:** Restricted access to model and data

### Transparency and Explainability

#### Model Interpretability

**Decision Transparency:**

* **Feature Importance:** TF-IDF weights show which terms influence decisions
* **Confidence Scores:** Probability estimates indicate model certainty
* **Category Mapping:** Clear relationship between predictions and business categories

**Error Analysis:**

* **Pattern Recognition:** Common misclassification patterns identified
* **Root Cause Analysis:** Understanding why specific errors occur
* **Improvement Tracking:** Monitor error reduction over time

#### Human Oversight Integration

**Confidence-Based Routing:**

def route\_query(prediction, confidence\_score):

if confidence\_score >= 0.95:

return "automated\_routing"

elif confidence\_score >= 0.80:

return "automated\_with\_review"

else:

return "human\_agent\_required"

**Agent Support Features:**

* **Override Capability:** Agents can correct AI classifications
* **Explanation:** Show model confidence and key terms
* **Feedback Loop:** Agent corrections improve future performance

### Continuous Ethical Monitoring

#### Ongoing Assessment

**Monthly Reviews:**

* Performance consistency across query types
* Error pattern analysis and trending
* Agent feedback on AI decision quality

**Quarterly Assessments:**

* Comprehensive bias audit across available dimensions
* Customer satisfaction impact analysis
* Model fairness metrics evaluation

#### Improvement Framework

**Feedback Integration:**

* Human corrections fed back to model training
* Error pattern analysis drives preprocessing improvements
* Regular model updates incorporate ethical considerations

## Conclusion

### Project Summary

This customer query classification project demonstrates a systematic approach to developing production-ready ML solutions:

**Technical Achievement:**

* **98.71% F1-Score** through systematic model evaluation and optimization
* **Efficient Implementation** with fast inference and minimal resource requirements
* **Robust Validation** using cross-validation and comprehensive error analysis
* **Real-World Testing** with 95.3% average confidence on production data

**Practical Value:**

* **High Automation Potential:** 96% of queries can be handled with high confidence
* **Production-Ready Design:** Clear deployment path with monitoring considerations
* **Scalable Architecture:** Design supports growth and future enhancements
* **Cost-Effective:** Simple model achieves excellent results without complex infrastructure

**Responsible AI Implementation:**

* **Bias Awareness:** Systematic assessment of potential fairness issues
* **Privacy Considerations:** Data minimization and protection principles
* **Human-Centered Design:** Meaningful human oversight and intervention capabilities

### Key Technical Insights

**Model Selection:**

* Simple, well-tuned models often outperform complex alternatives
* Proper text preprocessing crucial for classification performance
* Cross-validation essential for realistic performance estimation

**Production Readiness:**

* Confidence scores enable intelligent routing decisions
* Error patterns provide actionable insights for improvement
* Monitoring framework essential for maintaining quality over time
* Real-world testing validates laboratory results

### Deployment Strategy

**Confidence-Based Automation:**

* **≥85% confidence:** Automatic routing (96% of cases)
* **70-85% confidence:** Automated with human review
* **<70% confidence:** Direct to human agents

**Monitoring Framework:**

* **Daily:** Accuracy and confidence distribution tracking
* **Weekly:** Error pattern analysis and category performance
* **Monthly:** Model performance review and retraining assessment
* **Quarterly:** Comprehensive bias audit and fairness evaluation

### Recommendations

**For Immediate Implementation:**

1. **Deploy with confidence thresholds:** High confidence (>95%) for automation
2. **Maintain human oversight:** Route low confidence queries to agents
3. **Monitor performance:** Track accuracy and error patterns continuously
4. **Collect feedback:** Use agent corrections to improve the model

**For Future Enhancement:**

1. **Active learning:** Systematic incorporation of human feedback
2. **Advanced models:** Explore transformer architectures for potential improvements
3. **Multilingual support:** Expand to handle queries in multiple languages
4. **Context integration:** Include customer history and interaction patterns

This solution provides a solid foundation for automated query classification while maintaining the flexibility to evolve with changing business needs and advancing ML capabilities.

**Repository Contents:**

* 01\_exploratory\_analysis.py - Data understanding and EDA
* 02\_data\_preprocessing.py - Text preprocessing pipeline
* 03\_model\_development.py - Model training and comparison
* 04\_model\_evaluation.py - Cross-validation and performance analysis
* 05\_model\_deployment\_testing.py - Production testing and deployment validation
* README.md - Setup and execution instructions

**Thank you for reviewing this solution. I'm happy to discuss any aspects in more detail.**