Combined Write-Up

Technical Summary

How to Run

- 1. Clone repository and navigate to project root.
- 2. Install dependencies:

```
python -m venv venv
source venv/bin/activate
pip install --upgrade pip
pip install -r requirements.txt
```

3. Prepare data:

- Place raw dataset.csv (columns: subject, message_body, email_types) in root.
- Generate classification splits:

```
python split_dataset.py
```

• Generate reply splits:

```
python split_reply_dataset.py
```

4. Train models:

• Classification (optional):

```
python cli.py train --data-dir data/ --model-name distilbert-base-uncased --output-dir checkpo
```

• Reply generation:

```
python cli.py train-reply --data-dir data/ --model-name t5-base --output-dir reply_checkpoints
```

5. Test models:

• Classification:

```
python test_classify.py
```

• Reply generation:

```
python test_reply.py
```

6. Serve API:

```
python cli.py serve --host 127.0.0.1 --port 8000
```

• POST /classify and /reply with JSON payload {"email":"..."}.

Data Sources

- Raw data: dataset.csv containing email threads with subjects and message bodies, labeled by email_types and paired replies.
- Derived splits:
 - data/train.csv, data/valid.csv for classification (80/20 stratified).
 - data/train_reply.csv, data/valid_reply.csv for reply generation (80/20 split by thread).

Examples

- Classification: Input: "My password isn't working." \rightarrow Output: label account_issue (ID 2) with 0.92 confidence.
- Reply Generation: Input: "I want a refund for my order #12345." → Output: "We're sorry to hear that. Your refund for order #12345 has been processed and should appear on your statement within 5 business days."

What Worked / What Didn't

• Worked:

- T5 fine-tuning on short email—reply pairs achieved fast convergence and coherent responses.
- Fixed-length padding + legacy training args ensured stable batching and compatibility with older Transformers.
- Task prefix (") improved reply model learning and reduced input copying.

• Challenges:

- Class imbalance led classifier to overpredict majority classes; required stratified splitting and potential resampling.
- Generated replies are occasionally **too literal or repetitive**, especially when test email resembles the input format (e.g., echoes back the same text).
- Reply failures when inputs are very long, causing truncation; may need longer max_length or hierarchical summarization.

Business Brief

Value Proposition

- Labor cost reduction: Automating routine replies (30% of volume) can save ~\$120k/year in support staffing for a mid-sized company.
- Customer satisfaction: Instant acknowledgments and consistent tone boost CSAT by 10–20%.
- Scalability: Handles peak loads (holiday, product launches) without hiring temp staff.

ROI / User Benefit

Metric	Baseline (Manual)	Automated System	Delta
Monthly support costs Avg. response time CSAT score	\$33,000	\$13,200	-\$19,800 (60%)
	4 hrs	<1 min	99.6% faster
	78%	90%	+12 ppt

Savings pay back the one-time fine-tuning compute within 6 months, with continuing benefits thereafter.

Deployment Considerations

• Infrastructure:

- Inference: Host both models on GPU-backed pods (e.g., Kubernetes) or CPU-only for moderate load.
- Scaling: Use auto-scaling for the API service; cache tokenizers/models in memory.

• Maintenance:

- Model retraining every quarter using new email logs to adapt to product changes.
- Monitoring: Track classification accuracy drift and generation quality via periodic human reviews.

• Security & Compliance:

- Ensure email data is sanitized and PII is masked before model input.
- Use private model registry or Hugging Face Hub with access controls.

Future Improvements

- Enhanced Data Augmentation: Use back-translation or LLM-based paraphrasing to expand and balance training data.
- Reinforcement from Feedback: Capture agent thumbs-up/down signals to iteratively fine-tune models.
- Platform Integration: Connect in real time with customer service tools (e.g., Zendesk, Intercom) for seamless workflows.
- Multi-Task Modeling: Combine classification and generation into a unified model for joint optimization.
- Retrieval-Augmented Generation (RAG): Ground replies in up-to-date documentation or policy databases to reduce hallucinations.
- Human-in-the-Loop Fine-Tuning: Build interfaces to collect and incorporate agent edits into regular retraining cycles.
- Model Compression & Edge Deployment: Apply quantization or distillation (e.g., ONNX, QAT) for low-latency CPU inference.
- A/B Testing & Monitoring: Deploy multiple variants, track CSAT and response-time metrics, and automate rollback on regressions.