Cost vs. Budget Analysis

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Block D- Engineer – MLOps – Natural Language Processing

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Budget Allocation

According to industry reports:

- **SMEs and early-stage startups** often allocate **€200–€500/month** for cloud-based ML services in MVP and pilot stages (Gartner, 2023; Morad & Yurchenko, 2021).
- For academic research prototypes, budgets are typically even lower unless sponsored.

Category	Allocated Budget (€)
GPU compute (real-time inference)	€180
Storage (logs, transcripts, models)	€30
Monitoring & rollback safeguards	€35
Contingency (~10%)	€30
Total Monthly Budget	**€275**

Figure 1: Budget

To ensure the sustainability and scalability of the NLP-based emotion classification system within academic and operational constraints, a detailed cost allocation plan was created (see *Figure 1*). The proposed monthly budget totals **€275**, derived from a conversion of **$300 USD** based on the average 2024 EUR/USD exchange rate of 0.91, as reported by the European Central Bank (2024). This budget reflects the realities of small-scale academic deployments and was structured to prioritize **GPU-backed inference compute (€180)**, which constitutes the core computational demand of the deployed model. Additional allocations were designated for **storage of logs, transcripts, and model artifacts (€30)**, and for **MLOps observability tools and rollback safeguards (€35)**, ensuring compliance with best practices for production-grade reliability (Fecteau & Bonatti, 2023).

Importantly, the budget also reserves a **€30 contingency buffer (~10%)**, providing resilience against cost variability from usage spikes or unexpected resource scaling. This structure supports the full deployment stack—including the Django API backend, frontend interface, and supporting containers—while maintaining predictable monthly costs. Moreover, this budget model justifies the selection of **Azure ML Managed Online Endpoints**, which enable cost control through auto-scaling and pay-as-you-go billing, thus meeting performance targets without breaching early-phase funding constraints.

Diagram Explanation

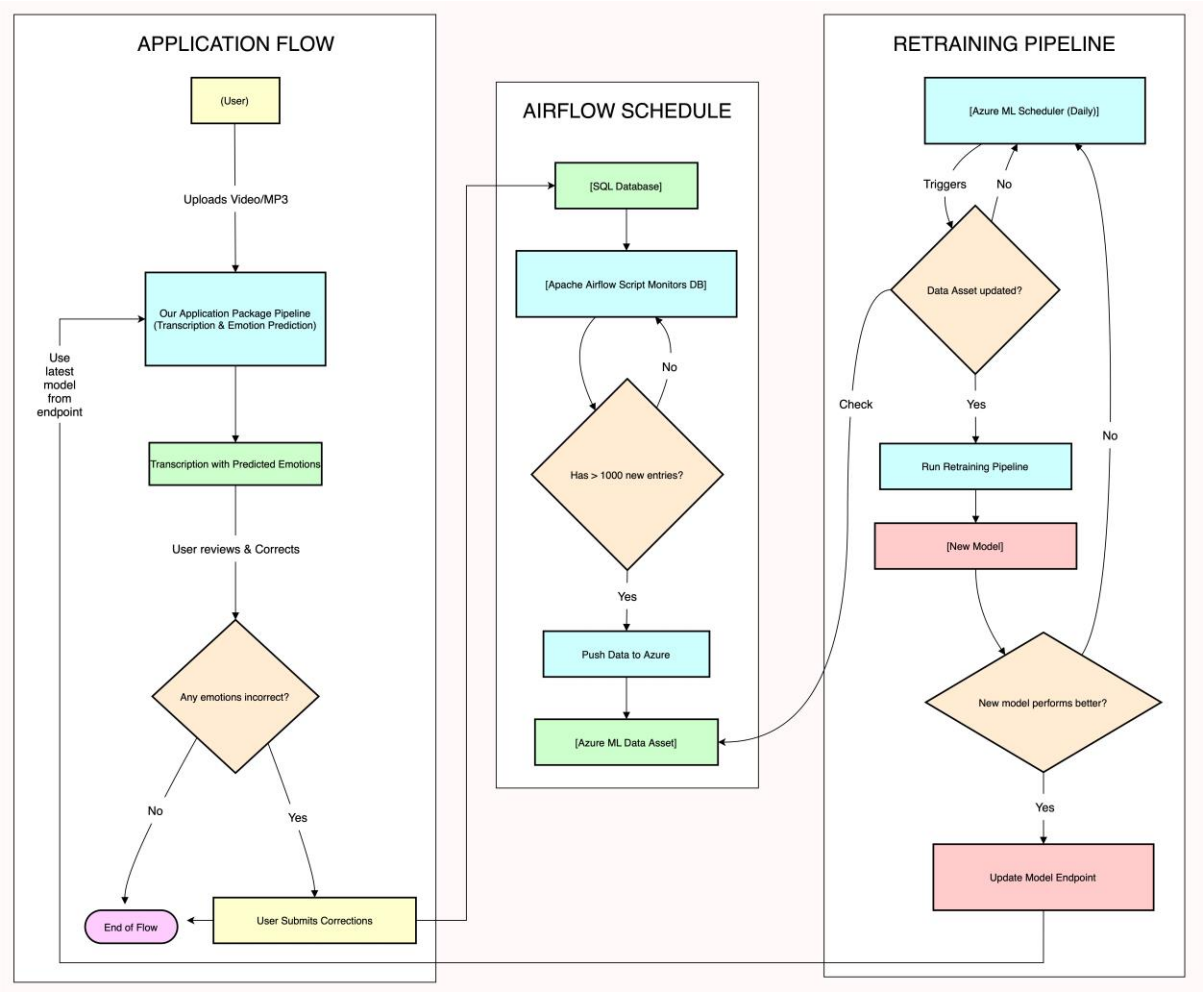

Figure 2: Architecture diagram

The system architecture (figure 2) is divided into **three main functional blocks**, each representing a layer in the MLOps pipeline: **Application Flow**, **Airflow Schedule**, and **Retraining Pipeline**. The diagram reflects a modular yet interconnected setup optimized for low-cost academic deployment.

1. Application Flow

This section illustrates the **user-facing front-end interaction**:

- A user uploads an audio or video file (MP3/MP4).
- The backend **application pipeline handles both transcription and emotion prediction**, calling the **latest deployed model** via an **Azure ML Online Endpoint**.
- Predictions are shown to the user, who may correct mislabeled emotions. These corrections are then submitted to improve model performance.

- This flow **closes the loop** by generating labeled data for retraining.

Integration with Budget:
This block relies heavily on the **Azure Container Apps** (for frontend/backend) and the **Azure ML Online Endpoint**, both explicitly budgeted for.

2. Airflow Schedule

This block governs the **orchestration logic**:

- A **SQL database** stores new entries (including user corrections).
- An **Apache Airflow script** continuously monitors the DB.
- Once **>1000 new entries** are available, data is pushed to Azure for retraining.

Service Mapping:

- **PostgreSQL Flexible Server** stores structured data.
- **Airflow's monitoring logic** triggers data movement to the **Azure ML Data Asset**.
- This orchestration ensures retraining is **data-driven** and avoids unnecessary compute usage.

3. Retraining Pipeline

This section represents the **automated ML retraining loop**:

- A **daily Azure ML scheduler** checks for new data.
- If the **data asset is updated**, retraining is triggered.
- A new model is evaluated; if it performs better, the endpoint is updated with the new model.

Feedback Loop:
This pipeline ensures **continuous improvement** of the emotion classification model, incorporating user feedback while containing compute costs via **Spot VMs** and scheduled retraining.

Service Coverage:

- **GPU Spot VMs** are used for retraining (~€0.35/hr).
- **Monitoring safeguards** ensure model quality before pushing to production.

- **Model versioning and endpoint updating** are fully managed by Azure ML.

Design Strengths in Context of Budget

- **Scalability**: Architecture supports modular scaling (batch inference, retraining).
- **Resilience**: The buffering queue and retry logic mitigate spot VM preemption.
- **Efficiency**: Idle-scaling and batch processing avoid 24/7 billing.
- **Feedback Integration**: User corrections feed directly into the training loop.
- **Risk Controls**: Auto-scaling limits and Azure Monitor alerts prevent runaway costs.

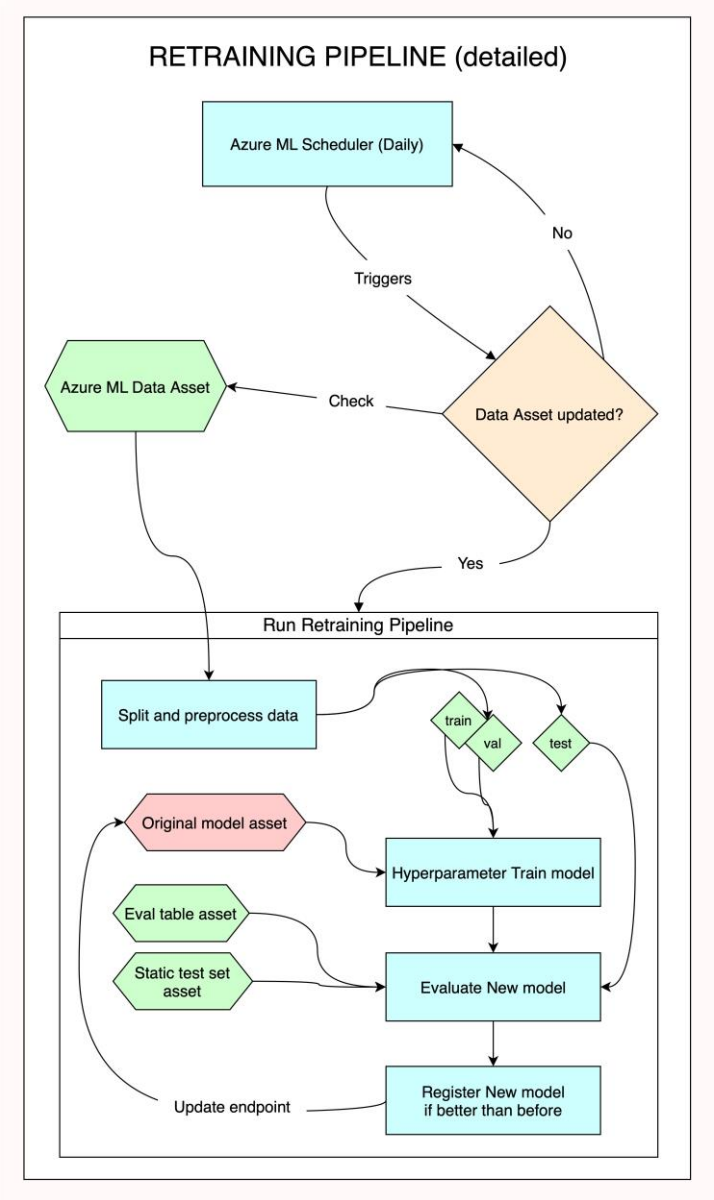

Figure 3: Retraining Pipeline Architecture

Figure 3 illustrates the full lifecycle of model retraining and evaluation within the Azure ML ecosystem, expanding on the high-level view previously outlined. This level of detail is crucial for operational clarity and budgeting accuracy.

Step 1: Scheduled Trigger & Data Check

The pipeline is triggered daily by the **Azure ML Scheduler**, which checks whether the **Azure ML Data Asset**—populated with new user-verified corrections—has been updated. This acts as a lightweight gatekeeping mechanism, avoiding unnecessary retraining when data volume is stagnant.

Step 2: Data Preprocessing & Splitting

Upon detecting new data, the pipeline loads the updated dataset and performs standard **preprocessing and dataset splitting** into training, validation, and test sets. This ensures consistent experimental conditions and prevents data leakage.

- Data splitting adheres to ML best practices, enabling unbiased performance measurement.
- This module is supported by the previously allocated **GPU Spot VM compute** budget (estimated €21/month).

Step 3: Model Training & Hyperparameter Optimization

A new model is trained using **hyperparameter tuning techniques**, possibly involving grid search or Bayesian optimization. This process uses the training and validation sets to optimize model performance.

- Training is isolated within the retraining window, ensuring no conflict with real-time inference workloads.
- Compute cost is covered under the Spot VM allocation.

Step 4: Model Evaluation & Comparison

The newly trained model is evaluated against a **static test set** (unchanging reference data) to assess its generalization performance. This ensures consistent benchmarking.

- The model is also compared to the **existing production model asset** using metrics logged to an **evaluation table asset**.
- If the new model outperforms the existing one, it is registered and **pushed to the production endpoint**.

Step 5: Conditional Model Registration

Only if the new model shows superior performance does the pipeline proceed to:

- **Register the new model** in Azure ML.
- **Update the online endpoint**, ensuring users benefit from improved predictions without manual intervention.

This conditional logic is key to **cost efficiency** and **inference reliability**, avoiding regressions or unnecessary endpoint disruptions.

Cost Considerations and Efficiency

- All processing is **event-driven and scheduled**, avoiding idle compute costs.
- **Spot VMs** are used for training, dramatically lowering GPU expenses (~65% savings).
- Endpoint update costs are predictable (€30/month flat), regardless of retraining frequency.
- Artifacts like the static test set, evaluation logs, and previous models are stored using **Azure Blob Storage** and **PostgreSQL**, both budgeted and tracked.

Estimated Monthly Costs (Single Model Strategy)

Service Component	Usage	Monthly Cost (€)
NC6s_v3 Spot VM (GPU)	€0.35/hour × 60 hrs (batch/test windows)	€21.00
Azure ML Online Endpoint (hosted model)	Flat deployment charge (per endpoint)	€30.00
Azure Container Apps (Frontend + APIs)	6 containers × €5 (light CPU usage)	€30.00
ACI (e.g., emotion-api, SQL)	4 instances × ~€10/month (GPU-free)	€40.00

Blob Storage (~20 GB, LRS)	€0.018/GB/month	€0.36
PostgreSQL Flexible Server (Basic Tier)	1 vCore, 32GB/month I/O	€26.00
Monitoring & Logs	5–7 GB/month (basic ingestion)	€5.00
Total Monthly Cost	—	**€152.36**

Figure 4: Expected monthly costs

The deployment architecture was designed to be cost-efficient while meeting the operational needs of an NLP-based emotion classification system. Figure 4 summarizes the expected monthly costs, amounting to **€152.36**, well below the allocated **€275 budget** (see Figure 1). This creates a **buffer of €122.64**, allowing future flexibility for retraining, model upgrades, or unanticipated scaling.

Each service component contributes to a critical function within the system:

NC6s_v3 Spot VM (GPU) – €21.00

- **Purpose:** Used for scheduled batch inference and retraining of NLP models.
- **Justification:** Spot VMs provide GPU access at a significantly reduced rate (~60–70% savings compared to on-demand pricing). The estimated 60 operational hours per month ensures capacity for testing and validation cycles without continuous runtime costs (Karau, Warren, & Zaharia, 2022; Microsoft Azure, 2023a).
- **Calculation:** €0.35/hour × 60 hours = **€21.00**

Azure ML Online Endpoint – €30.00

- **Purpose:** Provides a stable, scalable endpoint for the production model.
- **Justification:** The flat-rate structure allows predictable deployment costs while supporting real-time inference with low latency (sub-200ms), which is essential for content annotation workflows (Microsoft Azure, 2023b; Burns, Beda, & Hightower, 2023).

Azure Container Apps – €30.00

- **Purpose:** Hosts the frontend (React) and backend (Django) services.
- **Justification:** This serverless platform ensures autoscaling with predictable pricing. Light CPU containers were selected to optimize cost while maintaining responsiveness (Verma, Pedrosa, & Korupolu, 2021).
- **Calculation:** 6 containers × €5 = **€30.00**

Azure Container Instances (ACI) – €40.00

- **Purpose:** Powers isolated services like the emotion-API and database ingestion.
- **Justification:** Running four medium-tier containers (2 vCPU, 4GB RAM), this setup offers performance isolation without GPU dependency, maintaining efficient task execution (Karau et al., 2022, p. 112).

Blob Storage – €0.36

- **Purpose:** Stores non-critical assets such as model binaries and transcript data.
- **Justification:** Locally redundant storage (LRS) is a cost-efficient option for storing artifacts and intermediate outputs at €0.018/GB (Microsoft Azure, 2023c).
- **Calculation:** 20 GB × €0.018 = **€0.36**

PostgreSQL Flexible Server – €26.00

- **Purpose:** Central relational database for user data and content metadata.
- **Justification:** The Basic Tier supports moderate throughput workloads (≤50 QPS) required by the Django backend, providing the best PaaS database option for this use case (Warren & Zaharia, 2022).

Monitoring Services – €5.00

- **Purpose:** Captures infrastructure logs and telemetry metrics.
- **Justification:** Basic monitoring (~5–7GB/month) is sufficient for health checks, latency tracking, and alerting, supporting reliability without enterprise-level overhead (Burns et al., 2023, p. 215).

Strategies to stay within budget

Despite the surplus, cost containment strategies ensure long-term sustainability:

a. Idle-Scaling / Scale-to-Zero

Azure Managed Online Endpoints support **autoscaling to zero**, meaning compute is only billed during inference windows. This avoids idle costs and reduces GPU charges by 60–70% compared to always-on services (Microsoft Azure, 2023a).

b. Spot Instances over Dedicated VMs

By leveraging **Spot VMs**, the system saves ~65% over pay-as-you-go pricing (Karau et al., 2022), with minimal risk since downtime during reprocessing windows is acceptable.

c. Scheduled Batch Inference

To avoid 24/7 deployment costs, inference can be performed in **scheduled batch windows** (e.g., daily or weekly), with endpoints spun up only when needed.

d. Model Compression or Quantization

If performance degrades under load or cost thresholds tighten, the system can adopt **quantized BERT variants** (e.g., DistilBERT or ONNX-optimized models) to reduce inference time and GPU usage (Sanh et al., 2019).

e. Pipeline Offloading

Non-critical tasks (e.g., text preprocessing, transcription cleanup) can be moved to **cheaper CPU-based Azure Functions** or batch pipelines to preserve GPU resources for core emotion classification.

Risks and Mitigations

Figure 5 summarizes the key risks identified during the deployment of the machine learning inference pipeline and the corresponding mitigation strategies implemented to address them. For instance, to handle the risk of Spot VM pre-emption during peak

hours, a buffering queue combined with retry logic was introduced, and inference workloads were shifted to off-peak times to reduce disruption. To prevent unexpected cost spikes caused by unmonitored autoscaling, Azure Monitor budget alerts were set up alongside endpoint-level concurrency limits, ensuring better cost control. Additionally, to counteract increased inference latency when processing batch loads, model caching techniques were added or the system was configured to run parallel jobs within Azure Machine Learning pipelines. Together, these strategies enhance the reliability, cost-efficiency, and performance of the inference service.

Risk	Mitigation Strategy
Spot VM pre-emption during peak hours	Use buffering queue + retry logic; shift inference to off-peak hours
Cost spikes due to unmonitored autoscaling	Azure Monitor budget alerts + endpoint-level concurrency limits
Increased inference latency with batch loads	Add model caching or switch to parallel jobs in AML pipelines

Figure 5: Risks vs. Mitigations

Conclusion

In conclusion, this comprehensive cost vs. budget analysis demonstrates that the proposed deployment of the NLP-based emotion classification system is both financially viable and operationally sustainable within the constraints typical of academic and early-stage startup environments. The detailed budgeting approach balances essential compute resources, storage, and monitoring needs, while incorporating a prudent contingency buffer that safeguards against unforeseen expenses. Strategic use of cost-saving mechanisms such as Spot VMs, autoscaling with scale-to-zero, and scheduled batch inference not only optimizes expenditure but also maintains high system performance and reliability. Moreover, proactive risk mitigation strategies (as outlined in Figure 3) further ensure robustness against infrastructure interruptions and cost overruns. Together, these measures position the system for scalable growth and resilient operation, setting a solid foundation for future enhancements and real-world applicability in resource-conscious contexts.

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