**Project : Employee Sentiment Analysis**

**Q1. Why did we choose TextBlob over other sentiment analysis libraries like VADER or BERT for this project?**

We selected TextBlob because it is lightweight, easy to implement, and well-suited for prototyping sentiment analysis tasks. It requires no model training and provides quick polarity and subjectivity scores. However, this choice came with limitations: TextBlob isn't fine-tuned for corporate communication, unlike VADER, which is optimized for social media, or transformer-based models like BERT, which can be domain-adapted. A production-grade version of this project would require testing multiple models for accuracy and context-sensitivity.

**Q2. How does the monthly sentiment scoring method affect interpretation of employee engagement?**

Our monthly scoring method (+1, 0, -1) aggregates sentiment without considering message volume variations between employees. An employee sending 20 neutral messages will have a different impact on the aggregate score than one sending 3 highly negative messages. This scoring method risks masking patterns. Future improvement could normalize scores by message count or incorporate message intensity (e.g., weighting strong negatives more heavily).

**Q3. What are potential weaknesses in our flight risk detection method?**

We flagged employees sending 4 or more negative messages in a rolling 30-day window as flight risks. While this is a clear, easy-to-implement rule, it oversimplifies behavior patterns. For example, a generally engaged employee might send several negative messages during a stressful project period without intending to leave. Additionally, it ignores message severity or context. A future enhancement could factor in cumulative sentiment scores, message context, or engagement history.

**Q4. Why is relying on message length or word count as predictive features potentially misleading?**

In our regression model, we used message length and word count as features to predict sentiment scores. However, longer messages don't always imply more negativity or positivity. A short, direct message could be extremely negative, while a long message might be neutral or bureaucratic. Without testing feature correlation with sentiment labels, these features might introduce noise. Future models should include linguistic features like frequency of negative/positive words, sentiment intensity, or topic modeling outputs.

**Q5. How would labeling errors affect downstream tasks like employee ranking and risk detection?**

Inaccurate sentiment labeling propagates errors into every subsequent analysis — from scoring to ranking to flight risk detection. If TextBlob mislabels neutral complaints as positive, high-risk employees might go unnoticed. This highlights the importance of cross-verifying labeled outputs, using sample validation, and refining classification thresholds based on actual business communication samples.

**Q6. What ethical concerns should be considered when analyzing employee communications?**

Automating sentiment analysis on employee messages raises privacy and ethical questions. Even anonymized data can indirectly reveal personal or sensitive details. Using this analysis for HR decisions (like flagging flight risks) must be transparent, consent-based, and fair. Results should inform engagement initiatives, not punitive actions. Ethical AI guidelines and corporate data policies should guide such implementations.

**Q7. How could adding labeled training data improve the project outcomes?**

Our project operated on unlabeled data using unsupervised sentiment classification via TextBlob. Incorporating a small, manually labeled sample of corporate emails would enable threshold tuning, model validation, and potentially training of a supervised sentiment model tailored to internal communications. This would improve accuracy and allow adjustment for domain-specific language like corporate jargon, sarcasm, or formal complaints.

**Q8. Why is version control (like Git) valuable in projects like this?**

Maintaining project versions in Git enables collaborative updates, safe rollback to previous stages, and transparent tracking of changes. It also ensures reproducibility, which is crucial when validating AI-generated results or comparing performance across model iterations. For a sensitive HR analytics project, versioning provides accountability and traceability.

**Q9. What lessons about AI-human collaboration were learned through this project?**

This project demonstrated that AI models like TextBlob can efficiently automate initial labeling, but human oversight is vital for interpretation and validation. AI tools serve as collaborators, not decision-makers. Key analysis steps — such as defining thresholds, interpreting patterns, and ensuring fairness — require human judgment, domain knowledge, and context awareness.

**Q10. How would adding contextual features improve model performance?**

Currently, our predictive model used basic message metadata (length, word count). Adding contextual features like time of day, department, message subject line, or whether the message was a reply or escalation could significantly enhance model predictions. These features provide richer context around employee communication patterns and emotional triggers.