FINAL YEAR PROJECT PRESENTATION

Aspect Based Sentiment Analysis On Achieving Sustainable Work Environments Through Recommendation Model Using Job Review

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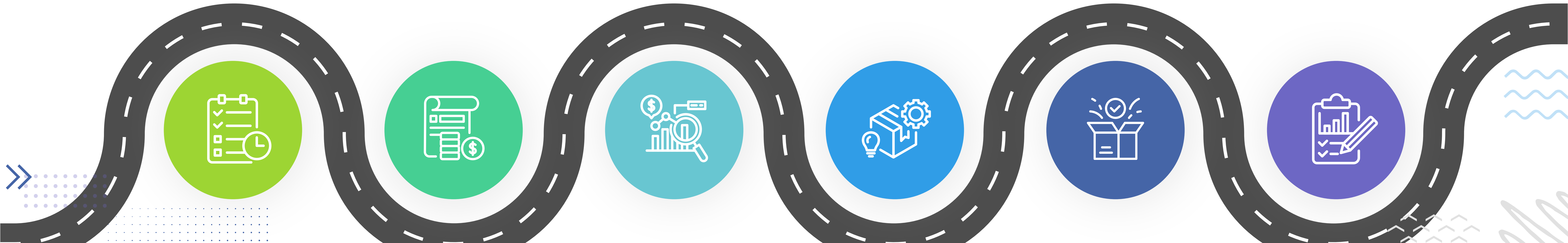


1. PROBLEM STATEMENT

Inefficiency and Inaccuracy of Annual Performance Reviews

Annual performance reviews consume over 210 hours of managerial time each year, yet they are often inaccurate and ineffective, with 77% of HR executives lacking confidence in their accuracy (Li, 2020).

Challenges in Analyzing Sentiment in Job Reviews

The sheer volume and complexity of job reviews, filled with nuanced sentiments, make them difficult to analyze accurately without automated sentiment analysis and topic modeling.

Addressing Work Environment Issues to Achieve SDG Goal 8

Improving the analysis of employee reviews through text mining and sentiment analysis is crucial for addressing workplace issues and achieving the Sustainable Development Goal of "Decent Work and Economic Growth" (SDG Goal 8).

2. AIM & OBJECTIVES

AIM

The project aims to analyze sentiment patterns in Glassdoor job reviews using Text Mining with Aspect Based Sentiment Analysis to improve workplace experiences and HR impact.

- OBJECTIVES -

- To **investigate** the **impact** of **HR practices** on the **sustainability** of **work environments** and the **relationships** between **HR initiatives** and employee **sentiment**, and **trends** through **job reviews.**
- To **conduct** a **comparative** and **temporal** investigation **analysis** of job reviews across different **companies** to **understand** variances in **sustainability** practices.
- To **develop** actionable **recommendations** model for **HR departments** to **enhance** workplace **sustainability** based on findings using **text mining** through **visualizations**.
- To **evaluate** the **performance** of the **machine learning models** in the Research Objective 3.

3. FUNCTIONALITY

Intangible Benefits

With **precise prediction**, it can foster a **positive work environment**, boost employee **morale**, and maintain a **favorable** company **reputation** among employees.

Tangible Benefits

Analyzing job reviews can gain insights into candidate experiences, helping HR make more informed **hiring decisions** and enhance **employee satisfaction.**

Quantifying sentiments can guide recruitment efforts by identifying areas for improvement which **optimize recruitment strategies** and **increase productivity**.

Target Users

Job seeker can **compare** different companies and **gain** authentic sentiments based on job reviews left.

HR professionals that can use **sentiment analysis** to **improve recruitment processes**.

Managers and team leads **benefit** from **specific insights or features** to foster a **positive work environment**.

Executives and **decision-makers** can leverage **recommendations** to make **strategic decisions** in global scale.

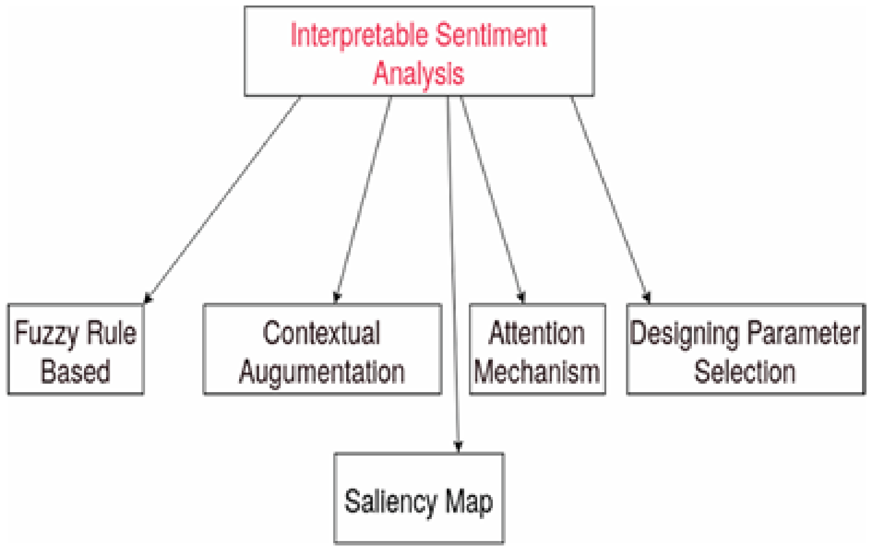
4. Literature Review

Sentiment Analysis in Job Reviews

- **Importance of Text Analytics**: Essential for **large-scale** text data analysis, such as job reviews, where **manual** analysis is **impractical**.
- **Sentiment Analysis Approaches**:
  - Document-Level
  - Sentence-Level
  - Aspect-Based

Interpretable AI for Sentiment Analysis

Provides **transparency** and **accountability** in model predictions, which is **crucial** for legal, medical, and financial domains.



Machine Learning Models for Sentiment Analysis

- **Common Models**:
  - Logistic Regression
  - Support Vector Machine (SVM)
  - Naive Bayes
  - Deep Learning Models (LSTM, CNN)
  - FastText
- **Challenges**: Models need a significant amount of labeled data and may not handle sentiment complexity well.

Similar Systems / Works

Key Findings:

- Few models **incorporate** recommendation features which can offer **actionable insights**.
- Most studies use datasets **smaller** than **10k** rows, which may **limit** generalizability.
- Incorporating both **textual** reviews and **ratings** can provide more **nuanced** analysis.
- No **Interpretable AI** was used and **Advanced Machine Learning** implementation on **Keyword Extraction**
- Only **one** study highlighted the use of **undersampling**.

5. Brief Description Model and Design

02

Keyword Extraction Model

The keyword extraction “**KeyBERT**” model **identifies** important **keywords** and **phrases** from **job reviews** based on its relevancy and rankings to the document’s embedding using cosine similarity.

03

Co-Occurrence Analysis

Co-Cccurrence analysis **examines** how **frequently pairs of keywords appear together** in job **reviews**. This helps in **understanding** the **relationships** and **associations** between different **topics** or **keywords**.

Data Labeling (Predict Sentiment) using **BERT** and **Keyword Extraction** using **KeyBERT** -> **Data Balancing** Based on Sentiments -> **Classification Model** Based on HAM/SPAM Problem (Headline: GOOD/BAD) -> **Deployment** of Models in Streamlit

Sentiment Prediction Model

01

The sentiment prediction model **categorizes** job **review** text as **positive** or **negative** to **understand** employees' **feelings** about the **workplace**.

Visualization and Recommendation

Visualization and recommendation are used to **present** the **results** of the **various models** in an **understandable** and **actionable** format. This includes generating **charts** and **graphs**.

04

6. Models’ Accuracies in Testing and Deployment

Sampling Method	Model Name	Test Accuracy
Undersampling (Python Script)	BERT Model	0.97
	SVM Model	0.94
	Logistic Regression Model	0.92
	Random Forest Model	0.91
	Naïve Bayes Model	0.93
Oversampling (SMOTE)	BERT Model	-
	SVM Model	0.96
	Logistic Regression Model	0.96
	Random Forest Model	0.96
	Naïve Bayes Model	0.94

By using classification report from sk_learn.metrics library, comparing test accuracies can be done easily.

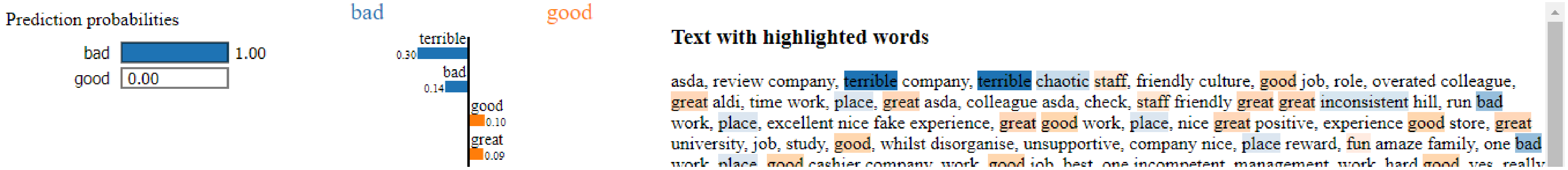
- The **BERT** model outperforms others with undersampling, indicating its robustness to class imbalance without needing synthetic data.
- **SVM** and **Logistic Regression** models perform similarly well with oversampling, suggesting that linear models benefit significantly from balanced datasets. **Random Forest** model shows consistent improvement with SMOTE, reflecting its ability to handle diverse datasets effectively. Lastly, **Naïve Bayes** model performs surprisingly well with undersampling and improves with oversampling, showing that even simpler models can benefit from balanced data.

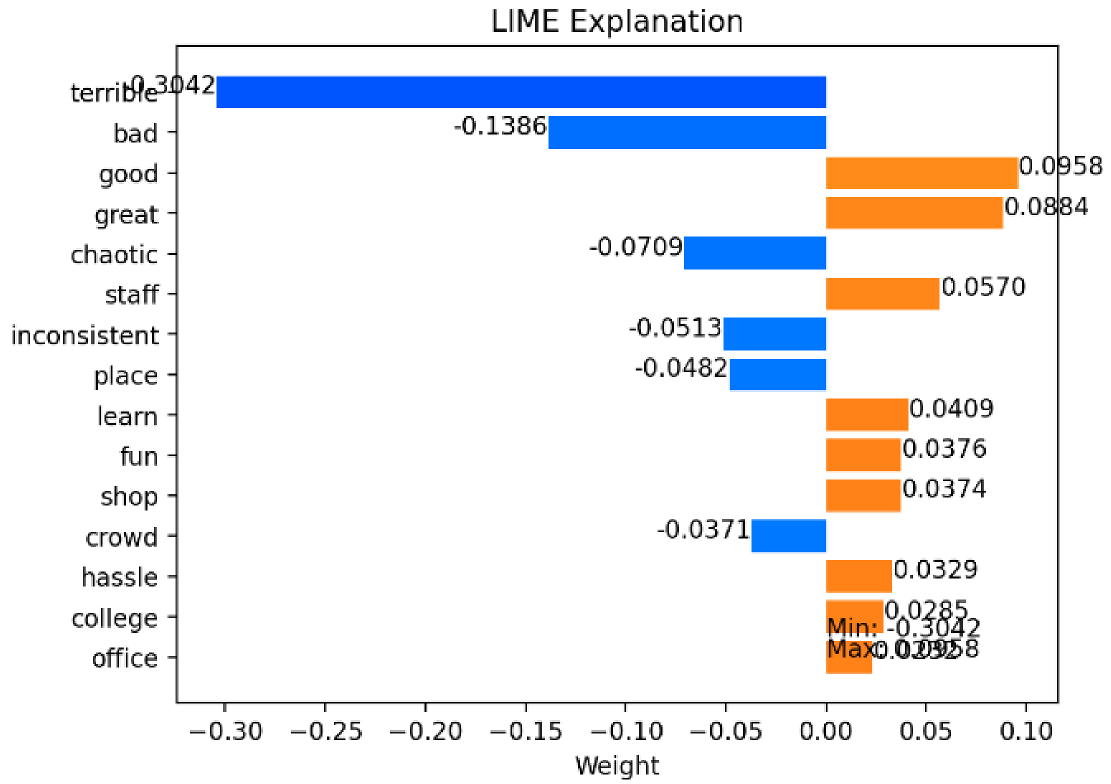
But how are these accuracies are reflected in the models’ deployment in Streamlit?

Predicted Sentiment

The predicted sentiment for ASDA is: bad

LIME Explanation





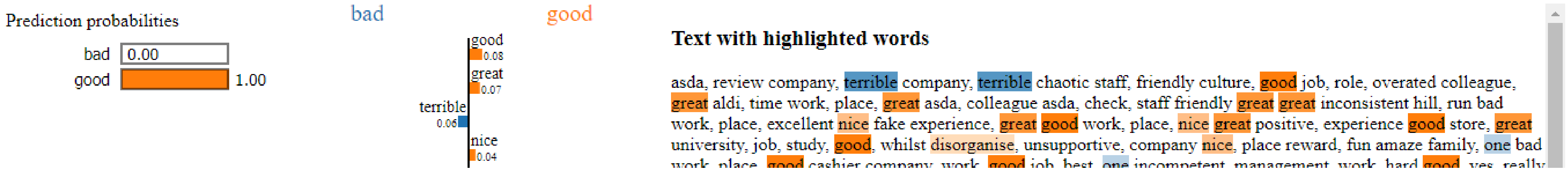
	Feature	Weight
0	terrible	-0.3042
1	bad	-0.1386
2	good	0.0958
3	great	0.0884
4	chaotic	-0.0709
5	staff	0.057
6	inconsistent	-0.0513
7	place	-0.0482
8	learn	0.0409
9	fun	0.0376

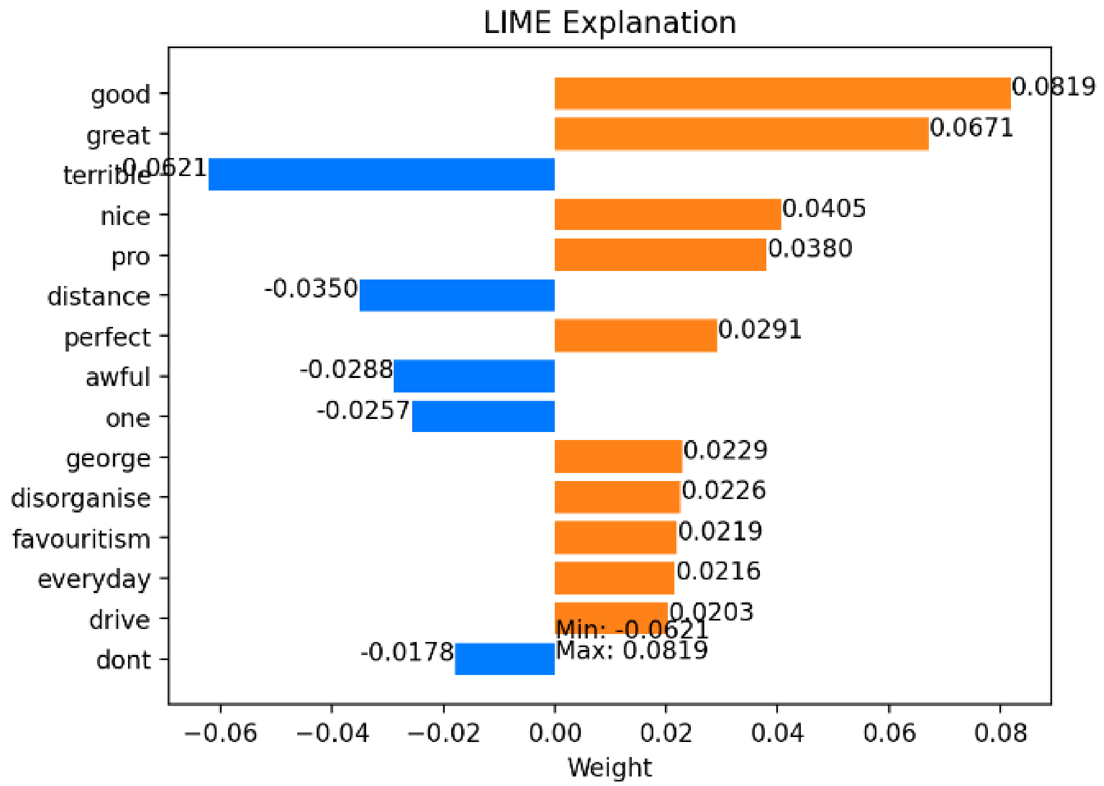
LIME explanation for BERT model is limited by reducing num_samples to 1000. By default, this number is around 5000.

Predicted Sentiment

The predicted sentiment for ASDA is: good

LIME Explanation





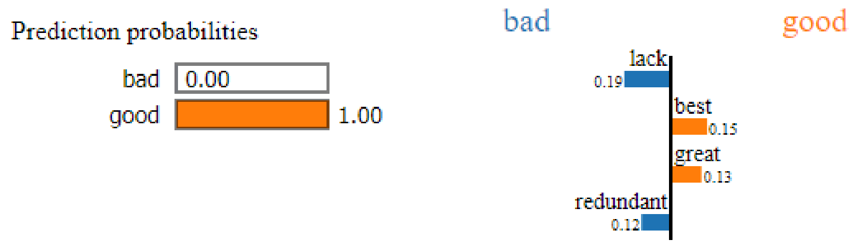
	Feature	Weight
0	good	0.0819
1	great	0.0671
2	terrible	-0.0621
3	nice	0.0405
4	pro	0.038
5	distance	-0.035
6	perfect	0.0291
7	awful	-0.0288
8	one	-0.0257
9	george	0.0229

The first company chosen for sentiment prediction is **ASDA**.

Predicted Sentiment

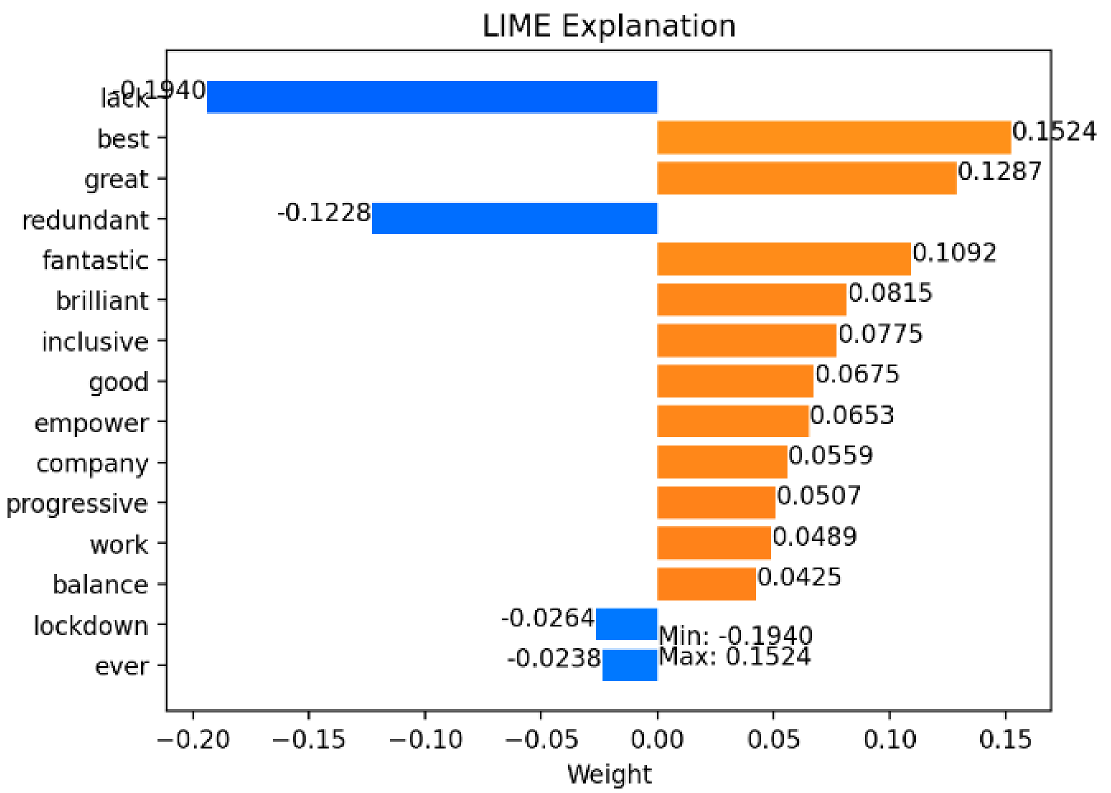
The predicted sentiment for AXA-UK is: good

LIME Explanation



Text with highlighted words

best, place, work, ever lockdown, redundant, make, great company, great, work experience, personal, base company, good inclusive, company, brilliant company, dor, work, great employee, look axa, recommend, health, work, place company, progressive, dynamic, work employer, fantastic company, brilliant trust, respect, support, empower review work, balance, life, progression, lack



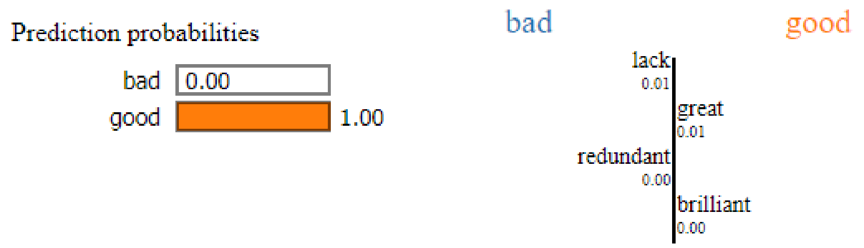
	Feature	Weight
0	lack	-0.194
1	best	0.1524
2	great	0.1287
3	redundant	-0.1228
4	fantastic	0.1092
5	brilliant	0.0815
6	inclusive	0.0775
7	good	0.0675
8	empower	0.0653
9	company	0.0559

The second company chosen for sentiment prediction is **AXA-UK**.

Predicted Sentiment

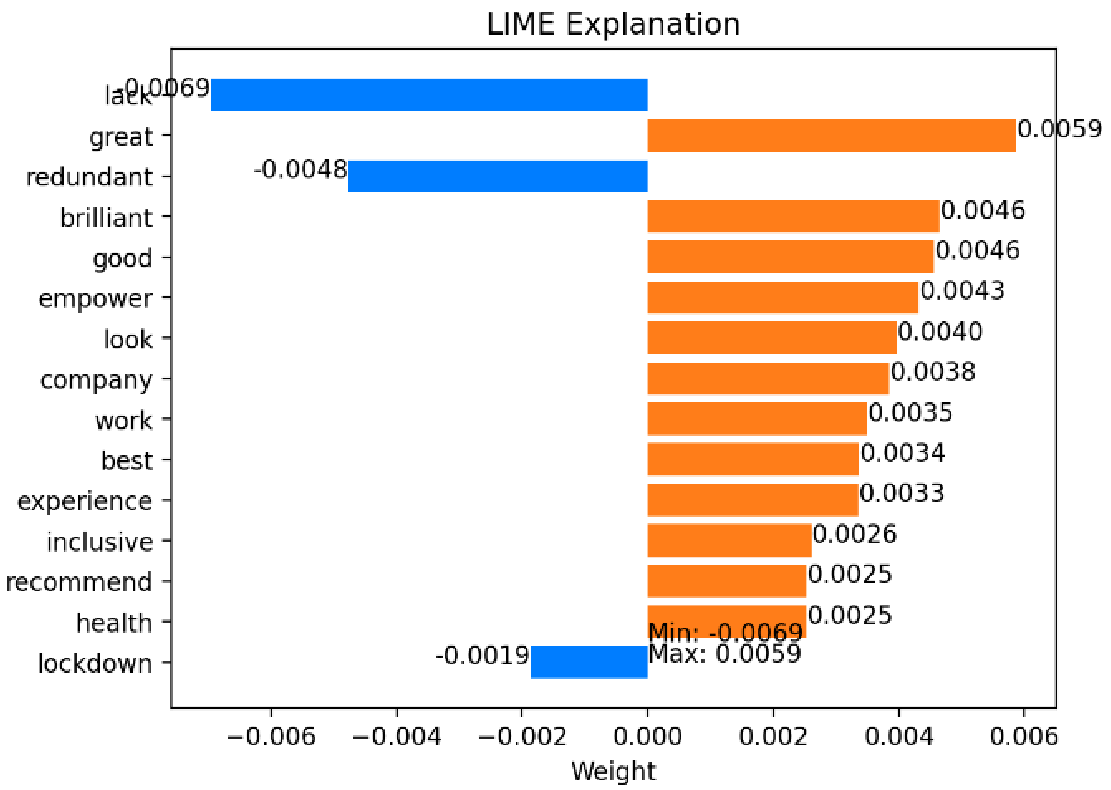
The predicted sentiment for AXA-UK is: good

LIME Explanation



Text with highlighted words

best, place, work, ever lockdown, redundant, make, great company, great, work experience, personal, base company, good inclusive, company, brilliant company, dor, work, great employee, look axa, recommend, health, work, place company, progressive, dynamic, work employer, fantastic company, brilliant trust, respect, support, empower review work, balance, life, progression, lack



	Feature	Weight
0	lack	-0.0069
1	great	0.0059
2	redundant	-0.0048
3	brilliant	0.0046
4	good	0.0046
5	empower	0.0043
6	look	0.004
7	company	0.0038
8	work	0.0035
9	best	0.0034

Despite lower num_samples, it still reaches the same prediction, and similar distribution in its weights.
Therefore, the previous result is not an error. With BERT bIdirectional training, it is able to understand words in the context of the review better.

7. Problems Encountered and Solutions

01

Data Representativeness

The data values are often **incompatible** and had to be **encoded** for training purposes which can be solved by **data preprocessing** and **postprocessing**. This includes but not limited to removing noise data, lemmatization, data balancing, etc.

02

Class Imbalance

Through **undersampling** and **oversampling** techniques, class **imbalances** are tackled, improving model **accuracy** for **less represented** sentiment **categories.**

03

Computational Resources

Advanced **pre-trained** models like **BERT** are **resource-intensive** for **training** and **deployment**. This can be tackled by **limiting** num_samples and num_features for LIME, as well as using GPU to speed up process.

04

Data Handling in Real-Time

To get a **quick analysis** and **visualizations** for current reviews and sentiment analysis, **Streamlit** is used which **supports real-time data** updates through reruns, filtering, APIs, caching, plots and charts.

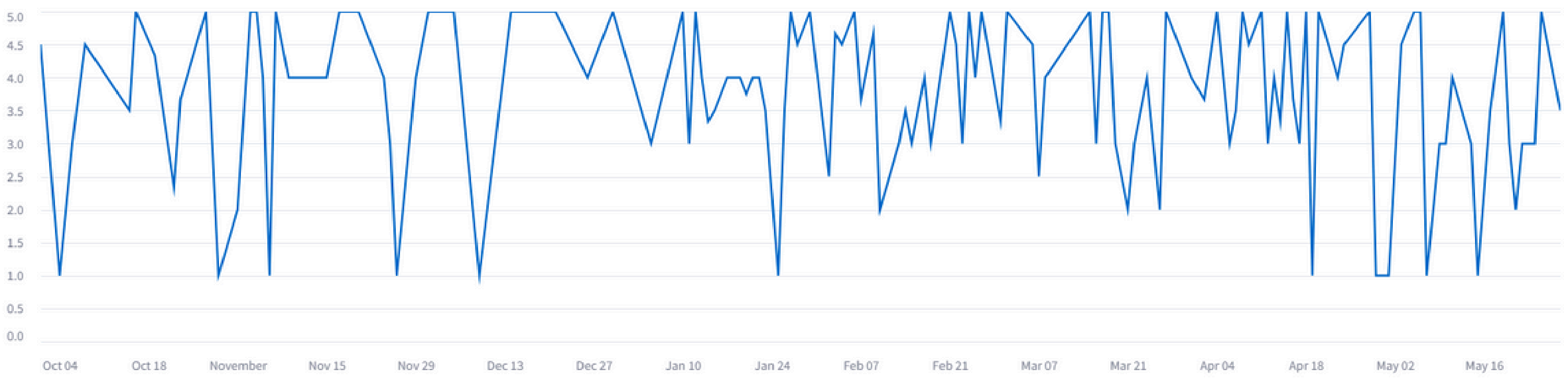
8. Success Criteria

Comparative & Temporal Analysis

01

Comparative analysis can be used to **compare** results of **different** chosen companies. Meanwhile, **temporal analysis** shows the **development** of the reviews ratings **over time.**

Sentiment Trends for ASDA



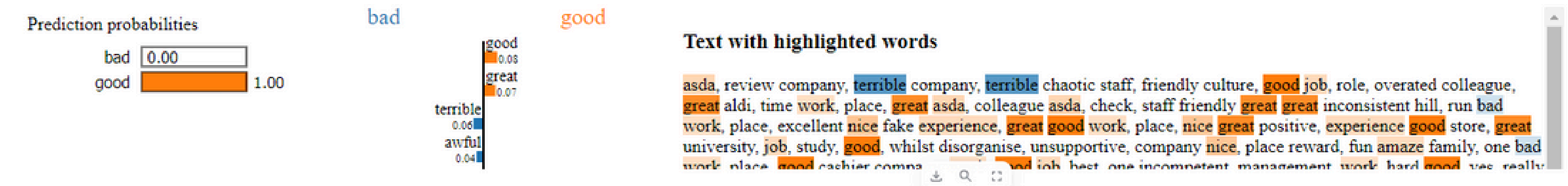
Comparative Analysis

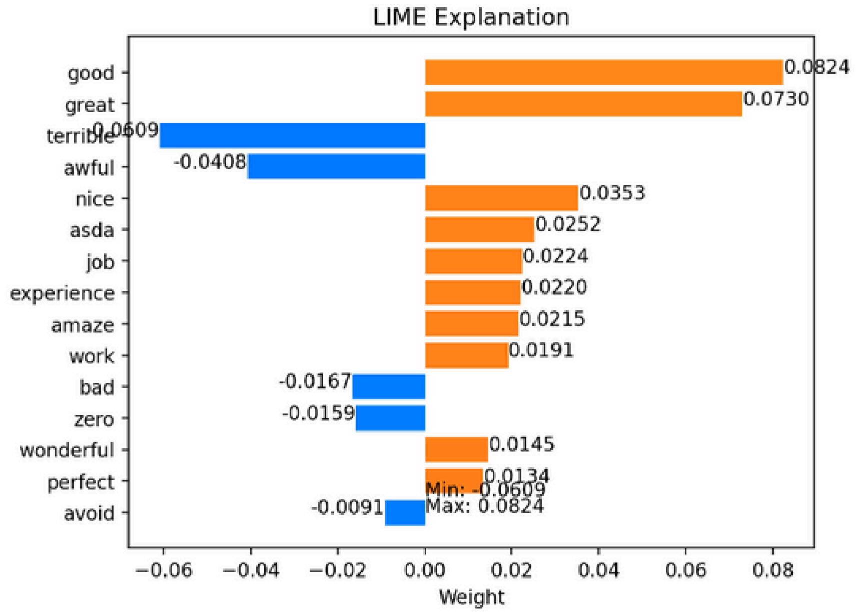
Comparative Analysis of Firms:

	firm	senior_mgmt	comp_benefits	work_life_balance	culture_values	diversity_inclusion	career_opp	Overall Score
1	ASDA	3.2898	3.4602	3.4545	3.6023	3.892	3.3239	3.5038
0	AFH-Wealth-Management	1	1	1	2	1	1	1.1667

Explore trends in sentiment over time and compare different companies based on their sentiment scores. This tab helps in understanding how sentiment evolves and how companies stack up against each other.

LIME Explanation





	Feature	Weight
0	good	0.0824
1	great	0.073
2	terrible	-0.0609
3	awful	-0.0408
4	nice	0.0353
5	asda	0.0252
6	job	0.0224
7	experience	0.022
8	amaze	0.0215
9	work	0.0191

Aspect-based sentiment analysis using **LIME** can identify **sentiments** related to specific **aspects** or **features** (or in this case, **Keywords**) within the text.

02

Aspect Based Sentiment Analysis

9. Success Criteria

Recommendation Systems

03

Various quick recommendation system dashboards related to either **HR personnels** and/or **job seekers**.

User Recommendations

Select criteria for recommendations:

Job Titles

Based on job titles:

Top job titles for AFH-Wealth-Management:

job_title	count
Client Engagement Executive	1

Top job titles for ASDA:

job_title	count
ASDA Colleague	15
Checkout Operator	9
Sales Assistant	9
Customer Assistant	7
Anonymous Employee	6

HR Recommendations

Select HR Insight:

Improve Workplace Culture

Recommendations for improving workplace culture:

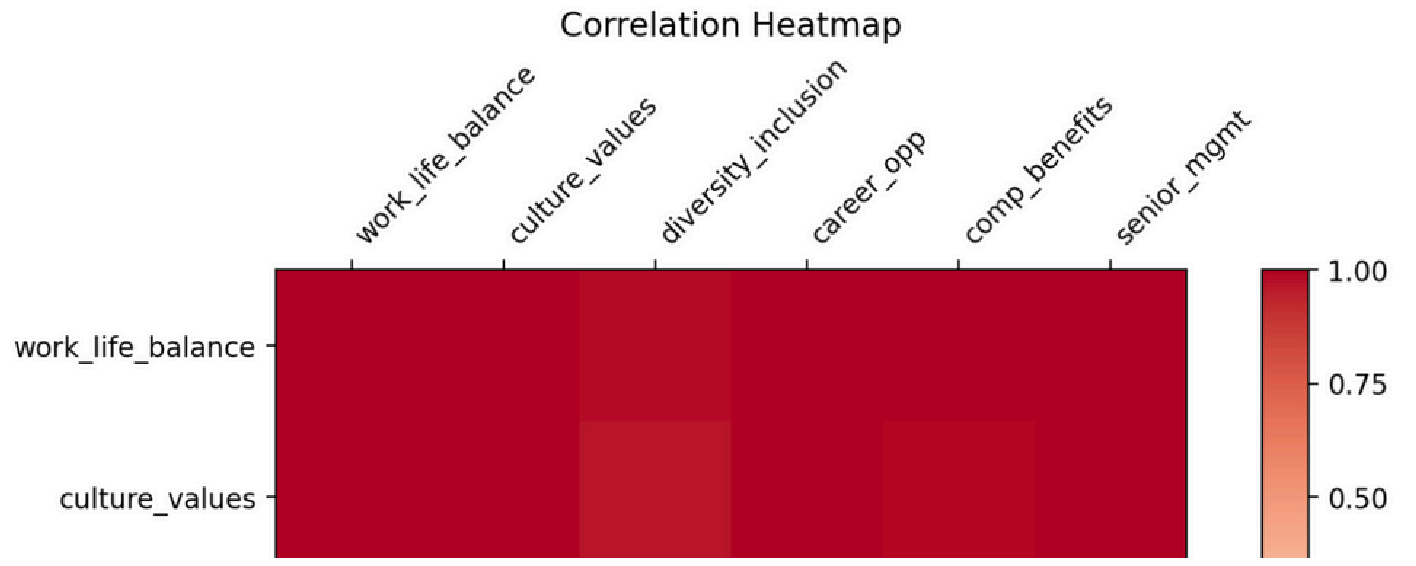
Culture feedback for AFH-Wealth-Management:

culture_values	count
2	1

Correlation Analysis

Correlation Matrix:

	work_life_balance	culture_values	diversity_inclusion	career_opp	comp_benefits	senior_mgmt
work_life_balance	1	0.9977	0.9798	0.9984	0.9963	0.9999
culture_values	0.9977	1	0.964	0.9922	0.9882	0.9965
diversity_inclusion	0.9798	0.964	1	0.9896	0.9933	0.9829
career_opp	0.9984	0.9922	0.9896	1	0.9996	0.9992
comp_benefits	0.9963	0.9882	0.9933	0.9996	1	0.9976
senior_mgmt	0.9999	0.9965	0.9829	0.9992	0.9976	1



Correlation and **co-occurence analysis** are able to gives enhanced understanding regarding the companies' **cultures** through other **features**.

04

Correlation and Co-Occurrence Analysis

10. Future Enhancement

01

Dataset Expansion

Incorporate data from various job review **platforms** and **industry** reports to enhance **representativeness** and **generalizability**.

02

Class Imbalance

Address class **imbalance** using **advanced** oversampling **techniques** like adaptive synthetic sampling/**ADASYN** or **ensemble methods**.

03

Advanced Model Architectures

Explore **advanced** **architectures** such as **transformers** and **hybrid** **models** to improve performance.

04

Streamlit App Enhancement

Integrate real-time data **handling** and **provide** comprehensive **user** **training** and **support**.

11. CONCLUSION

This project uses **sentiment analysis** of **job reviews** through **machine learning** to provide actionable insights using **Interpretable AI** that enhance **hiring decisions**, **employee satisfaction**, and **recruitment strategies**. By quantifying sentiments, it aids the target users in improving **workforce productivity**, **morale**, and **company reputation**, contributing to more effective organizational strategies and better employee experiences.

THANK YOU