Risk Events and Risk Behaviour Windows Detection with LSTM Model

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1. OVERVIEW AND OBJECTIVE

Lloyds Banking Group (LBG) faces internal fraud risks which could endanger customer well-being and internal stability. **This project aims to develop an unsupervised modelling framework to detect risk events and risk behaviour windows in LBG employees' spending activities**. **Comparison of Long-Short Term Memory (LSTM) models** are conducted to obtain the model that best captures the long-term dependencies of the data. Threshold computations, false positive (FP) pruning, and weekend effect will also be explored to address seasonal and trend effects in the series.

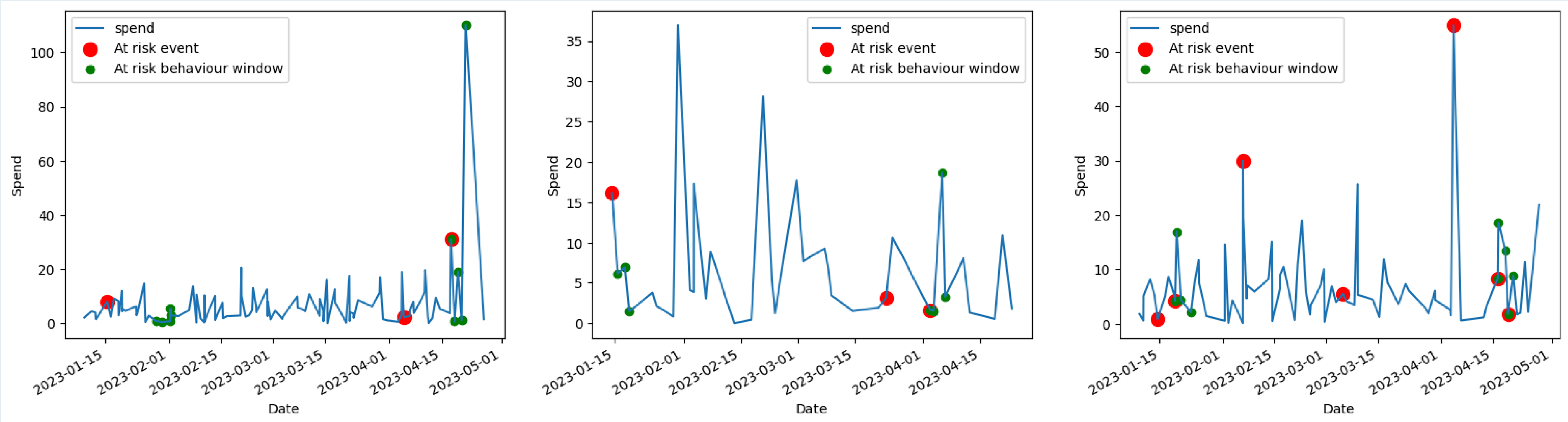

Fig 1. Risk events and risk behaviour windows of individual 1 (left), 100 (middle), and 1734 (right)

2. DATA

- Panel data of spending amounts for 2185 employees including dates, days of the week, time stamps, and department
- The two target variables:
  a. Risk events
  b. Risk behaviour windows
- No clear relationship between risk events and risk behaviour windows
- High spending and weekend activities are more likely to be a risk

Weekend/ weekday	Number of transactions	Number of anomalies	Anomaly proportion
Weekend	5222	1373	26.29%
Weekday	100055	1398	1.40%

Tab 1. Summary of anomalous weekend spending

3. METHODS

A. MODEL FITTING

1. LSTM Model Fitting

$$f_t = \sigma(W_f \times x_t + U_f \times h_{t-1} + b_f)$$
$$i_t = \sigma(W_i \times x_t + U_i \times h_{t-1} + b_i)$$
$$o_t = \sigma(W_o \times x_t + U_o \times h_{t-1} + b_o)$$
$$c_t' = \tanh(W_c \times x_t + U_c \times h_{t-1} + b_c)$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot c_t'$$
$$h_t = o_t \cdot \tanh(c_t)$$

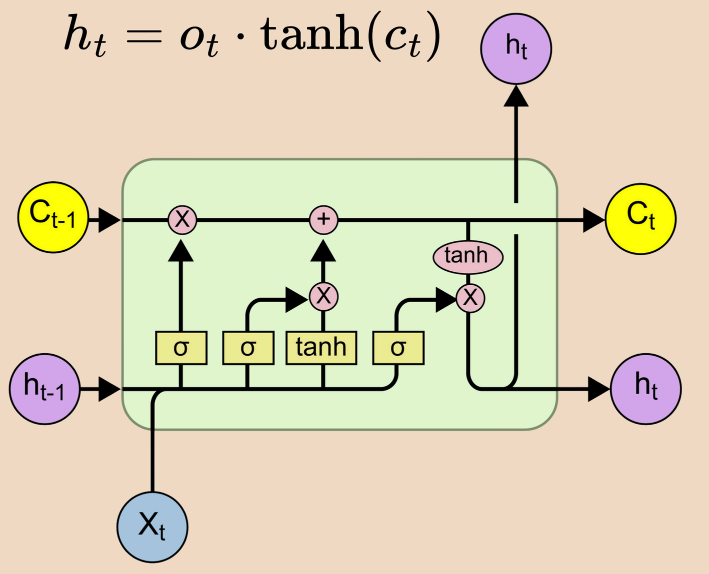

Fig 2. LSTM memory cell architecture [1]

2. Dynamic Threshold Computation [2]

Generate initial risk predictions:

$\mathbf{y}(i)$ is flagged as an anomaly if $\mathbf{y}(i) < \mathbf{h_L}(i)$ or $\mathbf{y}(i) > \mathbf{h_U}(i)$

$$\mathbf{h_U} = \bar{\mathbf{y}}_{train} + \beta\sqrt{var(\mathbf{y}_{train})}$$
$$\mathbf{h_L} = \bar{\mathbf{y}}_{train} - \beta\sqrt{var(\mathbf{y}_{train})},$$

B. POST-PROCESSING

1. False Positive (FP) Pruning [3]

a. Define set of error values $E = [e^{(t)}, e^{(t+1)}, \ldots, e^{(Q)}]$

b. Define $E_A = \{e^{(t)} \in E | \hat{y}^{(t)} \text{ is an anomaly}\}$

c. $y^{(t_1)}, y^{(t_2)}$ are not anomalies if $|e^{(t_1)} - e^{(t_2)}| < p$ and $|t_1 - t_2| < t_\Delta$

2. The Weekend Effect

A weekend activity is flagged as an anomaly if either:

1. It is the first weekend activity
2. The duration between the current weekend activity and its preceding weekend activity is longer than 29 days

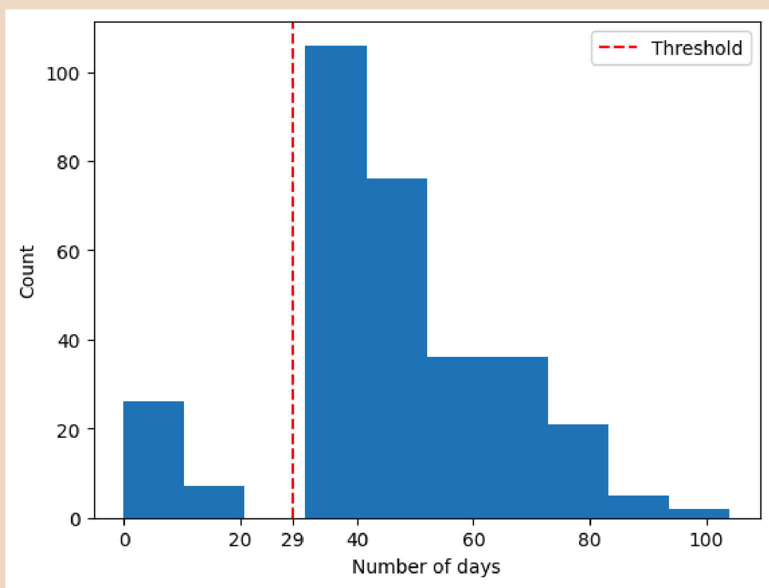

Fig 3. Histogram of the number of days between two consecutive anomalous weekend. Setting 29 days as the threshold appears to be optimal

4. RESULTS

- Model should be able to **accurately detect risky behaviours** to prevent unwanted loss and ensure stability and **refrain from raising excessive false alarms** to curb unnecessary costs and maintain user's trust level
- Hence, model selection is done based on the **F1 score** metric which captures the balance of both criteria

Risk Event Model	Threshold Computation Methods						Post-processing (Dynamic Thresh.)			
	Simple Quantile		Department-Based		**Dynamic**		FP Pruning		Weekend Effect	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Persistence model	16.45%	17.86%								
Univariate LSTM	**20.05%**	**19.79%**	21.56%	**20.55%**	**31.59%**	**31.08%**	31.64%	31.08%	**77.40%**	**74.46%**
Multivariate LSTM	19.75%	19.71%	**21.64%**	20.03%	28.78%	28.86%	28.84%	28.86%	75.01%	71.37%
LSTM Autoencoder	13.33%	14.73%	13.38%	14.40%	24.86%	23.46%	25.29%	23.54%	74.68%	70.94%

Tab 2. F1 scores for risk event target models. Highest F1 scores are highlighted in green.

Risk Behaviour Window Model	Threshold Computation Methods						Post-processing (Dynamic Thresh.)			
	Simple Quantile		Department-Based		**Dynamic**		FP Pruning		Weekend Effect	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Persistence model	8.26%	8.39%								
Univariate LSTM	**12.26%**	13.24%	**12.41%**	**14.22%**	**17.41%**	15.10%	15.10%	15.10%	**17.64%**	18.45%
Multivariate LSTM	11.46%	**14.03%**	12.34%	13.50%	15.98%	**16.87%**	16.87%	16.87%	16.76%	**18.87%**
LSTM Autoencoder	6.98%	8.78%	7.72%	9.16%	11.61%	12.78%	12.78%	12.78%	15.29%	17.49%

Tab 3. F1 scores for risk behaviour window target models. Highest F1 scores are highlighted in green.

5. CONCLUSIONS

- The **univariate LSTM model** with the **dynamic threshold** performs the best for identifying both targets
- **Risk event** model **sufficiently detects non-weekend effect anomalies. FP pruning** offers **improvements** and **most weekend effect anomalies** are **successfully identified** after **post-processing**
- **Underwhelming performance** of **risk behaviour windows** identification may be due to its **more complicated preemptive nature** than the more simplistic temporally instantaneous nature of a risk event
- **FP pruning is detrimental** and **weekend effect is not as influential** in determining **risk behaviour window**

Future Research

- Investigate more rigorous FP pruning algorithms and optimal window length determination techniques
- Explore more advanced time-series models or curve-fitting approaches to complex irregular temporal dynamics

REFERENCES

[1] C. Liu. Long short-term memory (lstm)-based news classification model. Plos one, 19(5):e0301835, 2024.
[2] R. Mo, Y. Pei, N. Venkatarayalu, P. Nathaniel, A. B. Premkumar, and S. Sun. An unsupervised tcn-based outlier detection for time series with seasonality and trend. In 2021 IEEE VTS 17th Asia Pacific Wireless Communications Symposium (APWCS), pages 1–5. IEEE, 2021.
[3] Y. Wang, X. Du, Z. Lu, Q. Duan, and J. Wu. Improved lstm-based time-series anomaly detection in rail transit operation environments. IEEE Transactions on Industrial Informatics, 18(12):9027–9036, 2022.