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**Paper Title :** Pattern Discovery and Forecasting of Attrition using Time Series Analysis

**Authors**: Saumyadip Sarkar, Dr. Rashmi Agarwal
REVA Academy for Corporate Excellence, REVA University, Bangalore, Karnataka, India

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# Plan of Presentation

# Introduction

- High Attrition (~ 34% avg. last 3 years)
- Missed SLAs – 278 in last 14 months
- Penalties - $2,082k for last 14 months


Forecast Attrition in advance → Plan workload management → Reduce Penalties

Transportation Line of Business

# Related work

20+ research papers and article are researched to understand employee attrition & timeseries forecasting related work.

## Key Findings

Attrition is a very costly affair for any industry. The direct costs of workforce turnover include the cost of hiring new employees, the cost of training new employees, the time it takes to transition, the cost of temporary employees, the cost of lost expertise, and the cost of the job itself (Chakraborty et al., 2021).

In the study (Kumar Jain et al., 123 C.E.) , several machine learning algorithms like Decision Tree, SVM, Random Forests have been used to estimate if an employee will leave or not.

There is one study that stands out from the rest is the use of Ensemble Model Based on Machine Learning Algorithms for automated employee attrition prediction (Alsheref et al., 2022).

In another study (Fallucchi et al., 2020), Gaussian Naïve Bayes classifier has been used to classify if an employee will attrit or not. XGBoost classifier has also been used to classify employee attrition (Jain & Nayyar, 2018).

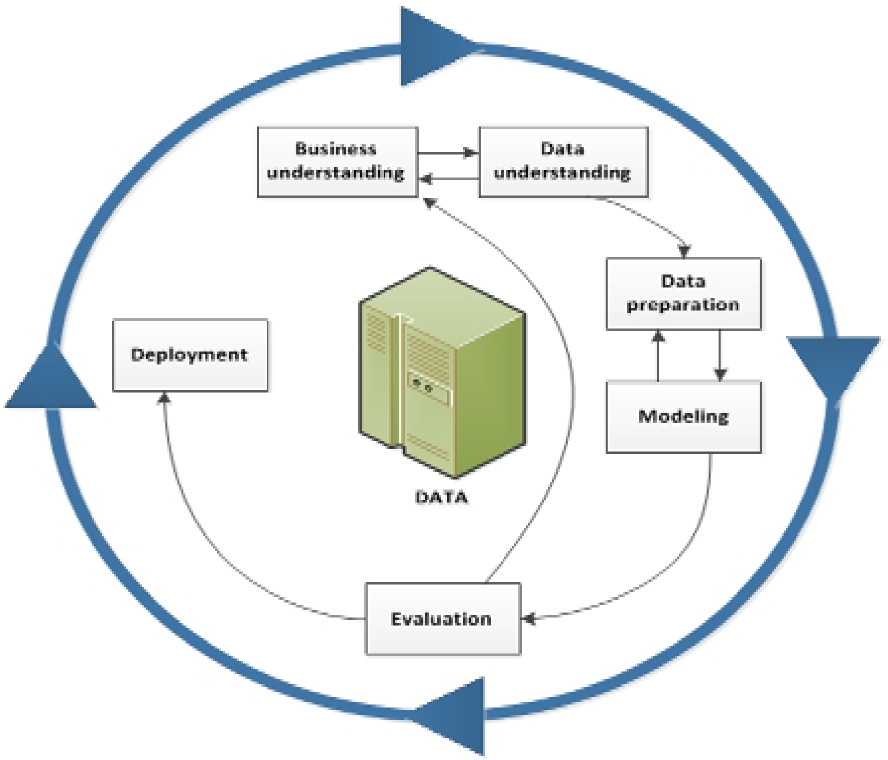
Time series analysis and forecasting are important for a variety of applications, including business, the stock market and exchange, the weather, electricity demand, cost, and usages of goods like fuels and electricity, etc., and in any setting where there are periodic, seasonal variations seen (Mahalakshmi et al., 2016) .

As seen in most of the studies related to attrition predictions, classification is the go-to approach. However, using time-series techniques to forecast future attrition has not been explored enough based on the observations during the literature review. **This establishes a unique opportunity for this study.**

# Methodology

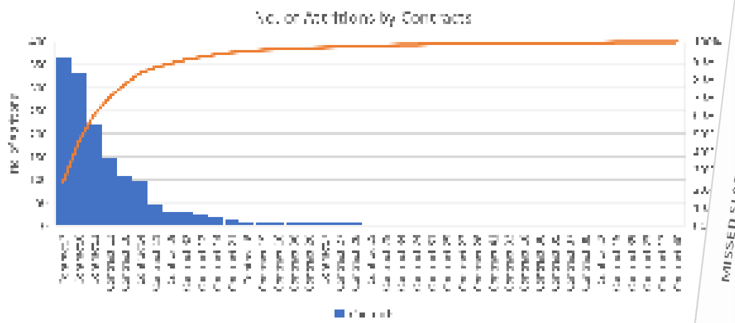
**CRISP-DM**

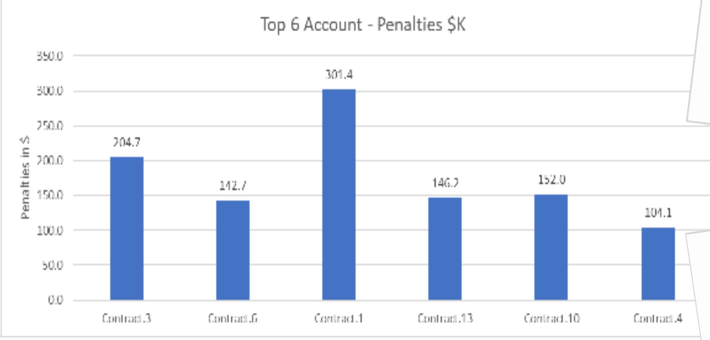
- Business Understanding – Transportation Line of Business
- Data Understanding – Attrition Data of last 14 months
- Data Preparation – Creating subsets by introducing various categories
- Modeling – Explore various timeseries forecasting models
- Evaluation – Compare results of various modeling techniques to identify the best one
- Deployment – Suggest a deployment strategy

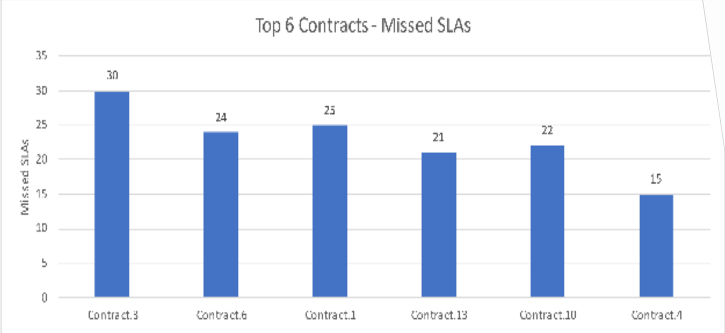


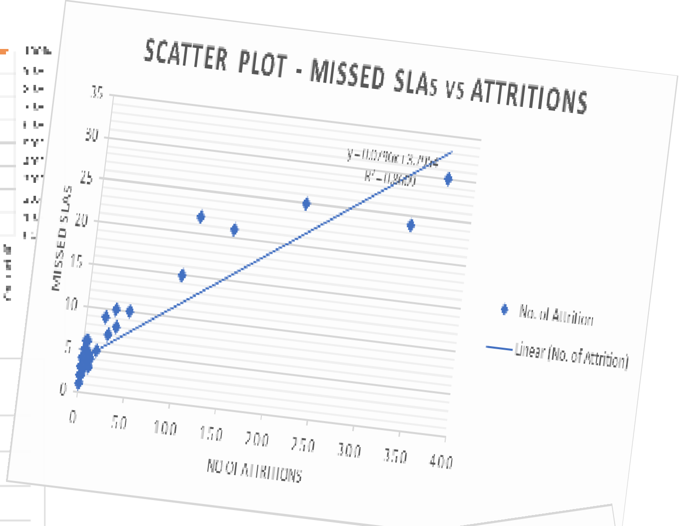
# Methodology

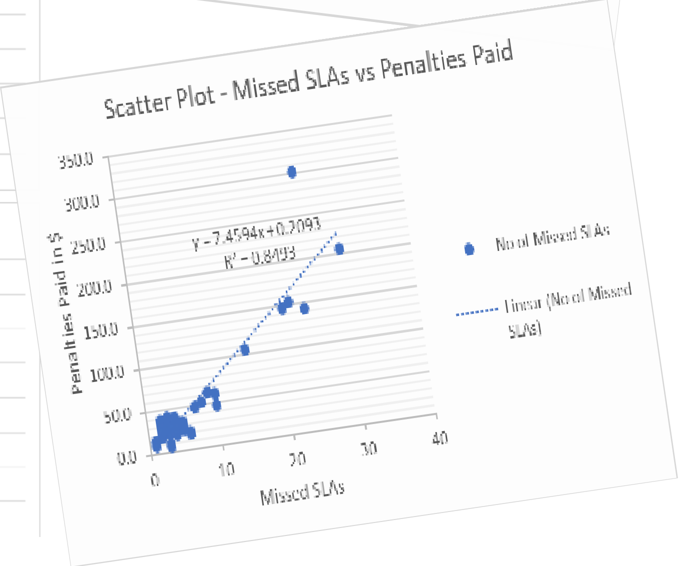
| | |
|---|---|
| **Key Findings** | Top 6 contracts which representing 15% of overall contracts are contributing to more than 80% of attrition and 50% penalties |
| | ~ 90% of attrition is happening at the junior most level (C01). Top 6 contracts remained constant. |
| | Top 11 cities representing 27 % contributed to 80% of attritions |
| | Salary ranging from \$20k to \$40k contribute to more than 80% attrition |
| | Strong correlation of 0.93 exists between contract level attrition numbers and missed SLAs |
| | Strong correlation of 0.92 is observed between Missed SLAs and Penalties paid at contract levels |





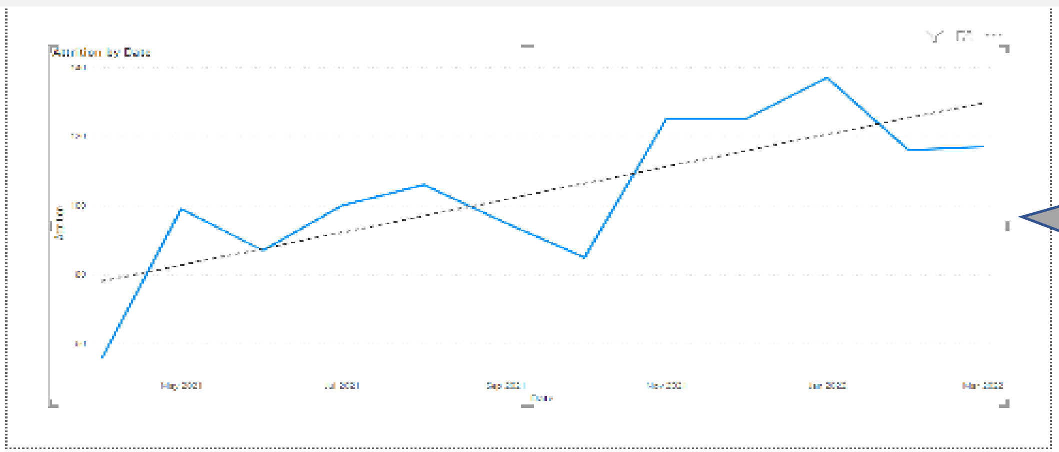



# Methodology

Dickey-Fuller Test → Data is Stationary Across all Dataset



Upward trend across all datasets contradicts Dickey-Fuller test

Following timeseries model are tested to validate both Stationary & Trend in the datasets

| Modeling Technique Used using MS Excel | |
|---|---|
| | Moving Average |
| | Ratio to Moving Average |
| | Exponential Smoothing |

| Modeling Technique Used using Python | |
|---|---|
| | ARIMA |
| | LSTM |
| | Holt-Winters |

# Methodology

| | |
|---|---|
| Moving Average | A 3 months moving average is considered as the data is divided into quarters consisting of 3 months<br>It is an empirical methods for smoothing and forecasting time-series |
| Ratio to Moving Average | Building on Moving Average, some additional steps are added like deseasonalizing the data, building regression model on the deseasonalized data to forecast<br>This method is frequently used to show the data's overall movement without taking seasonal effects into account. |
| Exponential Smoothing | MS Excel's FORECAST.ETS function is used<br>It uses AAA version of Exponential Smoothing<br>This method is based on three smoothing equations: stationary component, trend, and seasonal. |

# Methodology

**ARIMA**

- Auto ARIMA is used to find the best combination of the order (p,d,q)
- The best order found was (1,0,0).
- This order was used for all other datasets

**LSTM**

- The data is divided into train and test data and MinMax preprocessing technique is used on both the datasets
- LSTM learns using "TimeSeriesGenerator" function with input as 2.
- The Sequential, Dense, and LSTM classes are called from the Keras library
- The model is the run 50 epoch to understand the stage at which the loss is lowest for it to learn on its own

**Holt-Winters**

- Single HWES is used as the first technique.
- Double HWES is tried next with both additive and multiplicative for trend
- Finally Triple HWES is used with both additive and multiplicative for trend and seasonality

# Methodology

## Linear Regression

| Given forecasted attrition, missed SLAs are predicted using a linear regression model. | Similarly, with forecasted missed SLAs, the penalties are predicted using a linear regression model. |
|---|---|

| **Regression Formulae** |
|---|
| **Predicted Missed SLAs = (0.07958 * Forecasted Attrition) + 3.7954** |
| **Predicted Penalties = (7.45942 * Predicted Missed SLAs) + 0.20933** |

# Results & Discussion

ETS or Moving Average has the best MAPE across all the datasets.

| TS Models | MAPE | | | | | |
|---|---|---|---|---|---|---|
| | Overall Data | Top 6 Contracts | C01 Employee Level | Top 6 Contracts at (C01) | Top Salary Range | Top Cities |
| Moving Average (3) | 9% | 6% | 7% | 7% | 7% | 6% |
| Ratio to Moving Average | 12% | 11% | 13% | 12% | 9% | 12% |
| Exponential Triple Smoothing (ETS) | 10% | 6% | 4% | 4% | 2% | 4% |
| ARIMA | 14% | 14% | 15% | 19% | 13% | 15% |
| Holt Winters ES1 | 25% | 26% | 28% | 29% | 25% | 29% |
| Holt Winters ES2_ADD | 13% | 12% | 13% | 12% | 19% | 13% |
| Holt Winters ES2_MUL | 18% | 25% | 15% | 25% | 23% | 27% |
| Holt Winters ES3_ADD | 16% | 14% | 19% | 16% | 15% | 15% |
| Holt Winters ES3_MUL | 20% | 17% | 24% | 19% | 18% | 18% |

# Results & Discussion

The forecasting techniques were tested on the actual attrition data of the following two months.

Model Performance on Test Data

| Dataset | Forecasting Technique | MAD | RMSE | MAPE | MAPE during training |
|---|---|---|---|---|---|
| **Overall Data** | Moving Average | 25.8 | 28.6 | 17% | 9% |
| | ETS | 14.0 | 17.5 | 9% | 10% |
| **Top 6 Contracts** | Moving Average | 6.3 | 8.6 | 5% | 6% |
| | ETS | 7.1 | 7.6 | 6% | 6% |
| **C01 Employee Level** | ETS | 7.7 | 9.1 | 6% | 4% |
| **Top 6 contracts at (C01)** | ETS | 7.5 | 7.5 | 7% | 4% |
| **Top Salary Bucket** | ETS | 4.6 | 4.8 | 4% | 2% |
| **Top Cities** | ETS | 4.1 | 5.0 | 3% | 4% |

**ETS** is consistent during training & testing phase

# Results & Discussion

Forecasted attrition numbers are used for predicting Missed SLAs and Predicted Missed SLAs are used for predicting Penalties.

| Regression Formulae |
|---|
| **Predicted Missed SLAs = (0.07958 * Forecasted Attrition) + 3.7954** |
| **Predicted Penalties = (7.45942 * Predicted Missed SLAs) + 0.20933** |

Overall Data

| Month | ETS (Forecast) | Predicted Missed SLAs | Predicted Penalties in ($ k) |
|---|---|---|---|
| Month 1 | 128.7 | 14 | 104.9 |
| Month 2 | 133.4 | 14 | 107.7 |
| Month 3 | 138.2 | 15 | 110.6 |
| Total | | **43** | **323.2** |

| Regression Statistics (Y = Missed SLAs, X = Attrition) | |
|---|---|
| **Multiple R** | 0.93 |
| **R Square** | 0.86 |
| **Adjusted R Square** | 0.86 |
| **Standard Error** | 2.75 |

| Regression Statistics (Y = Penalties, X = Missed SLAs) | |
|---|---|
| **Multiple R** | 0.92 |
| **R Square** | 0.85 |
| **Adjusted R Square** | 0.85 |
| **Standard Error** | 23.18 |

# Future scope

- This time series technique for future attrition predictions needs to be carried out with future dataset to ascertain its validity.
- Other factors which might affect attrition can be introduced into the model.
- Early warning system can be developed to equip managers for proper workload management

# Conclusion

Given only attrition data, future attrition can be predicted with greater accuracy.

FORECAST.ETS
( MS Excel Function )

Consistent across all datasets

Simple & Easy to Use

Greater acceptability within organization

As with any modeling technique, continuous training with future attrition is recommended.

# References

Chakraborty, R., Mridha, K., Nath Shaw, R., & Ghosh, A. (2021). Study and Prediction Analysis of the Employee Turnover using Machine Learning Approaches; Study and Prediction Analysis of the Employee Turnover using Machine Learning Approaches. *2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON)*. https://doi.org/10.1109/GUCON50781.2021.9573759

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**Thank you**