# CHESS BLUNDER ANALYSIS USING MULTIVARIATE AND LINEAR ALGEBRAIC APPROACHES

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Abstract. This project provides a quantitative analysis of chess blunders using a large Lichess dataset and Stockfish evaluations. The research will study how temporal factors, positional complexity, piece dynamics, and player skill influence blunder probability, and propose modeling approaches (multivariate analysis, matrix factorization, and neural networks) for prediction.

## 1. Project Outline

1.1. **Description.** This project aims to conduct a quantitative investigation into the nature of blunders in the game of chess. Leveraging the large-scale Lichess open database (casual games, $\approx$ 90 million games/month) and the TWIC Archive (official international games, $\approx$ 8100 games/week), the research will analyze a significant dataset of games to identify the conditions under which players are most likely to make critical errors.

A "blunder" will be defined as a move that causes a substantial negative shift in the game's evaluation, as determined by the powerful Stockfish chess engine. The core of the investigation will be to correlate the occurrence of these blunders with a variety of contextual factors, including:

1. **Temporal Factors:** The amount of time remaining on a player's clock and the time spent on the move in question.
2. **Positional Complexity:** The "sharpness" or tactical complexity of the board state. This can be quantified by analyzing the win/draw/loss (WDL) probabilities provided by modern engines like Stockfish.
3. **Piece Dynamics:** The type of piece being moved (e.g., are blunders more common with knights than with rooks?).
4. **Player Skill Level:** How blunder frequency and type differ across various player rating brackets.

The ultimate goal is to move beyond simple blunder identification and develop a model that captures the interplay between these variables. The final phase of the project will involve an attempt to create a predictive neural network model that estimates the probability of a blunder occurring in a given position and context.

1.2. **Topic Fit.** The project integrates several core mathematical topics from the course:

- **Linear Algebra:** Board encodings, matrix factorizations (e.g., PCA, SVD) for feature reduction.
- **Probability and Statistics:** Modeling uncertainty in decision-making and empirical error distributions.
- **Graph Theory:** Representing chess positions as state-transition graphs.
- **Numerical Analysis:** Optimization and error minimization during model training.
- **Machine Learning:** Applying regression and neural models as practical extensions of linear methods.

*Date*: October 10, 2025.
2010 *Mathematics Subject Classification.* Primary .
*Key words and phrases.* chess, blunder, Stockfish, machine learning, multivariate analysis.

1.3. **Minimum Success Criteria.** A minimum successful outcome for this project would be the completion of a thorough descriptive analysis. This includes:

1. Successfully downloading, parsing, and processing a substantial subset of the Lichess database (e.g., 1 million games).
2. Analyzing these games with Stockfish to generate evaluation data for each move.
3. Producing a detailed statistical report with visualizations that clearly shows the relationships between blunder frequency and the key factors (time pressure, player rating, game phase, etc.).
4. A well-written final paper detailing the process and findings, even without a predictive model.

1.4. **Stretch Goals.** If the minimum outcome is achieved with time to spare, the project will proceed to:

- Extend the analysis to include neural network-based blunder prediction.
- Explore position-type clustering and visualization using dimensionality reduction.
- Compare models across player Elo ranges to study performance variance.

1.5. **Risk Mitigation.** The following table outlines potential risks and mitigation strategies:

| **Risk** | **Description** | **Impact** | **Mitigation Strategy** |
|---|---|---|---|
| Data Acquisition/Processing | The Lichess database is massive. Downloading and processing it could be slow and computationally expensive. PGN parsing can be complex. | High | Scope modification: start with a smaller subset (e.g., rapid games or a rating bracket). Use established libraries for PGN parsing. |
| Engine Analysis Time | Analyzing millions of moves with Stockfish can take days or weeks. | High | Reduce number of games, analyze only critical positions, or lower analysis depth. |
| Complexity of Predictive Model | Training a neural network can be time-consuming and complex. | Medium | Pivot to simpler models (logistic regression, XGBoost) if needed and focus on feature engineering. |
| Lack of Clear Correlation | Data may not show strong correlations between variables and blunder frequency. | Low | Treat the null result as informative; explore other factors or focus on interpretation. |

## References


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## 2. Final Paper Outline

**Note:** The Title, Abstract, Description/Introduction and References sections are already written above and do not need to be repeated here.

**Note:** Using subsections here but will be complete sections in the final paper.

### 2.1. Problem Formulation.

- Define blunders mathematically using Stockfish evaluation deltas ($> 150$ centipawns).
- Formal representation of features:
  - Position encoding as matrices/tensors.
  - Time and sharpness metrics.
  - Response variable: blunder occurrence probability.
- Notation and model assumptions.

### 2.2. Methodology.

- Data extraction from Lichess PGN datasets.
- Feature engineering using evaluation data and time metrics.
- Dimensionality reduction using PCA/SVD.
- Predictive modeling: regression and neural networks.
- Visualization of clusters using kernel-based similarity metrics.

### 2.3. Results.

- Empirical findings: correlation between time pressure and blunders.
- PCA projections showing dominant blunder factors.
- Predictive model accuracy and visualization of feature importance.

### 2.4. Conclusion.

- Key insights learned about player performance and cognitive limits.
- Discussion of open questions and extensions (e.g., player profiling, Elo-conditioned modeling).

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