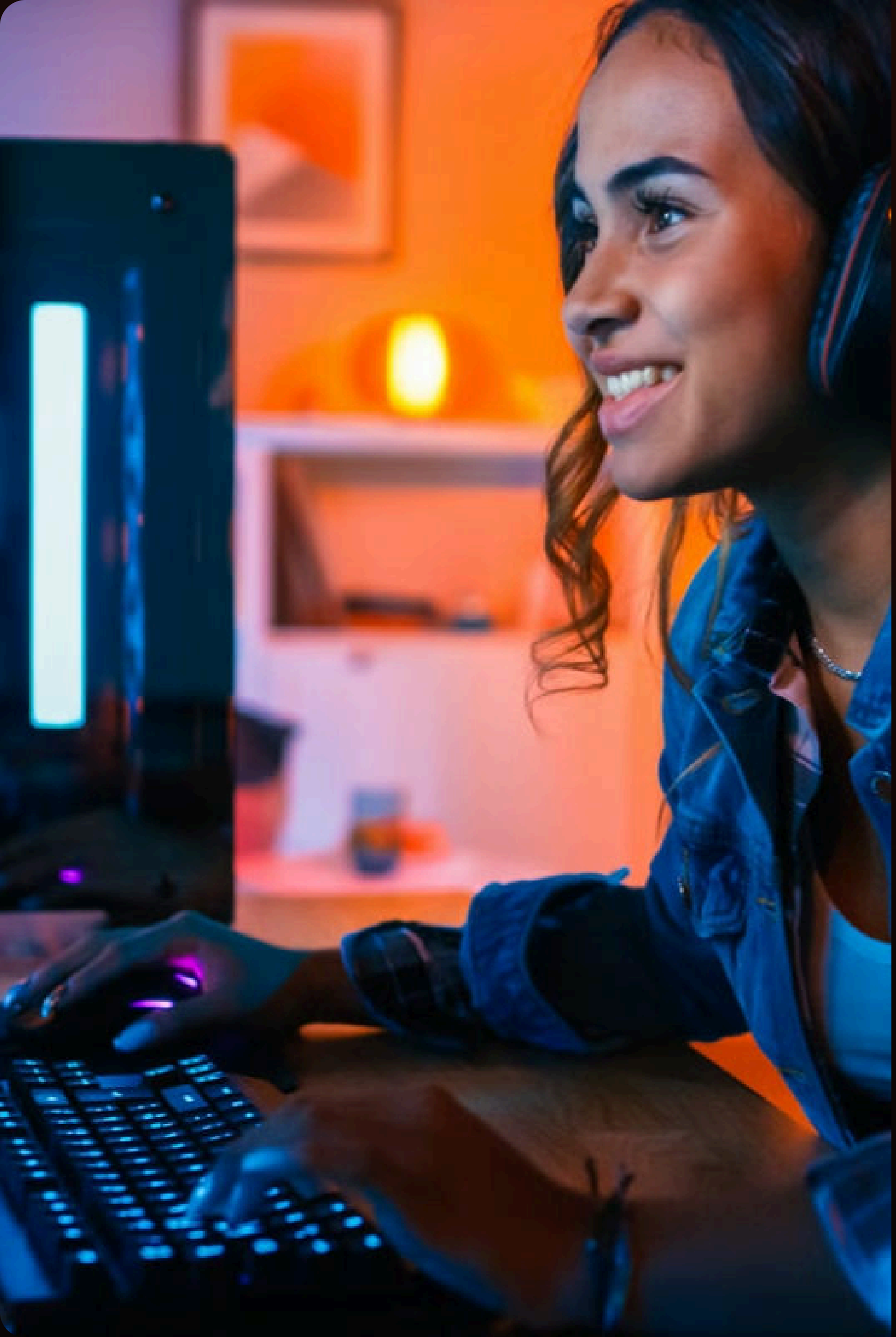


Matchmaking in Online Video Games

Matchmaking in online games aims to determine who should play together. It's complex, considering factors like skill, region, and behavior. We'll explore defining good matches and using machine learning to improve player experience.

by Juan Pablo Nieto

Challenges in Matchmaking

Matchmaking in online games faces various challenges. These include balancing skill levels, regional considerations, and player behavior.

Skill Balance

Ensuring players of similar skill levels are matched together.

Regional Factors

Considering geographical location to minimize latency issues.

Wait Times

Balancing match quality with acceptable queue times.

Pre-made Groups

Handling matchmaking for players in pre-formed teams.

Dataset and Preprocessing

1

Data Collection

Gathered data from 50,000 Dota 2 matches.

2

Cleaning & Exploration

Explored and organized data from 19 separate files.

3

Feature Engineering

Selected relevant features and created new ones for deeper insights.

4

Data Frames

Combined data into Matches, Players, and Minute-by-Minute breakdowns.

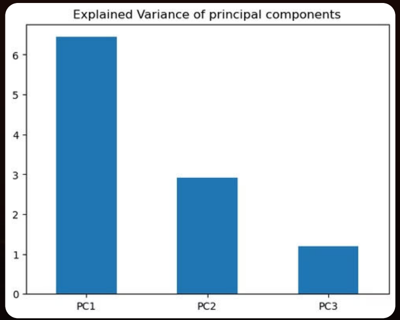
Defining Match Balance

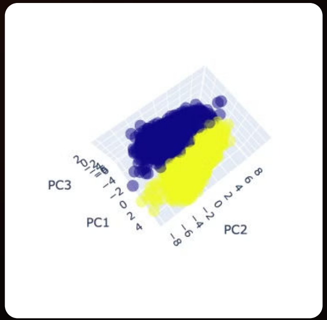
1 Clustering Attempt

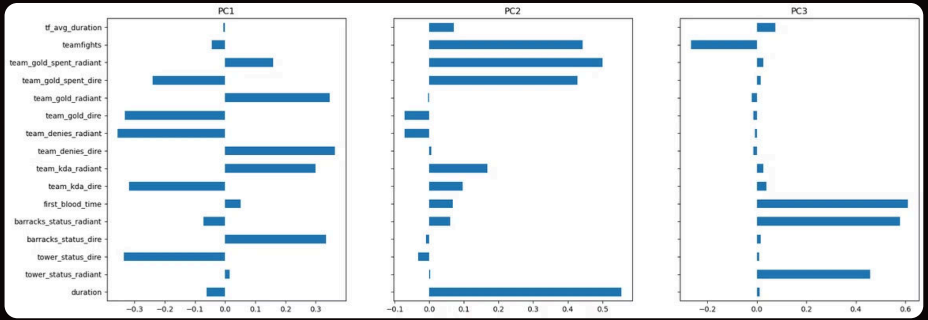
Unsupervised learning models used to identify match balance.

2 Limited Results

Only found clusters based on Radiant team winning or losing.







So What Is A Balanced Match In Dota?

> Your problem is a very hard task to answer. Esports hasn't figured out what performance metrics define a good performance, nor have we figured out what constitutes a bad performance. Ultimately there isn't much better than wins and losses.
>
> **Jesse Hart** - *Senior Director of Sports Science & Analytics @ Team Liquid*

TrueSkill System

TrueSkill, developed by Microsoft, estimates player skill levels based on match outcomes. It provides a measure of uncertainty for each player's skill.

Skill Estimation

Estimates player skill levels based on match outcomes.

Uncertainty Measure

Provides a measure of uncertainty for each player's skill.

Match Quality

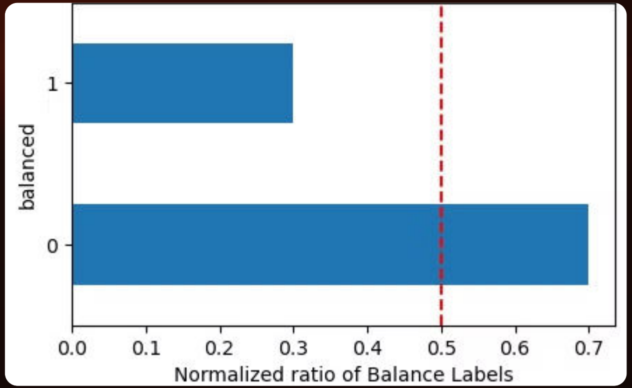
Can be used to rate match quality and predict balanced matches.

Limitations

Mainly focuses on past outcomes to determine skill level.

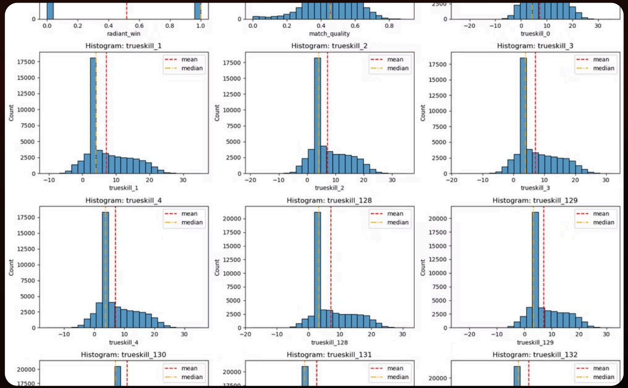
Exploratory Data Analysis

Initial EDA results were performed on the dataset. This analysis provided insights into the data structure and patterns.



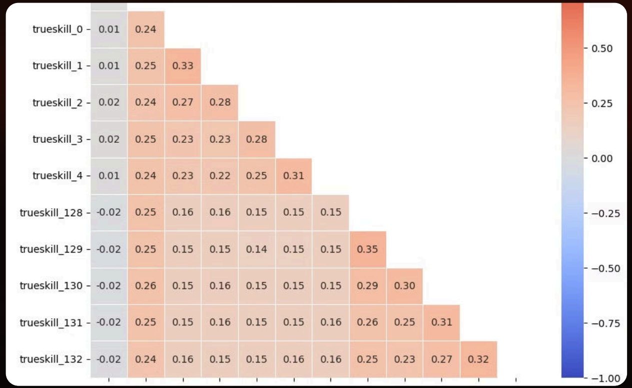
Target Distribution

Out of all the matches that were analyzed, only 30% of them were found to be balanced. This suggests that our dataset is imbalanced.



Statistical Analysis

Each feature displayed a normal distribution with slight disparities, suggesting that the underlying processes producing these variables are stable and predictable.



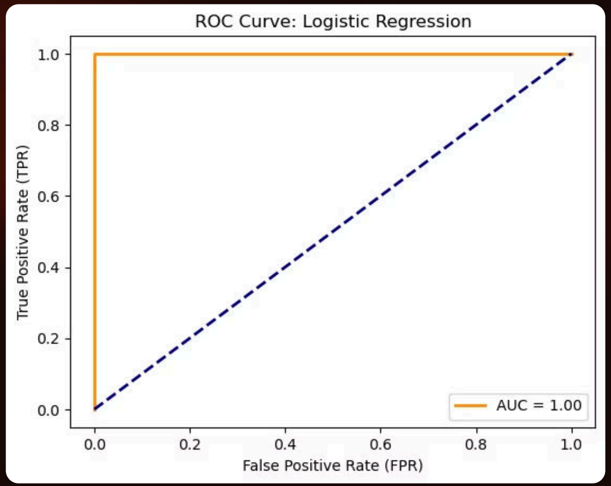
Feature Correlation

There is a low correlation between each player's skill level and the match outcome, while some moderate correlation exists between the skill levels of each player.

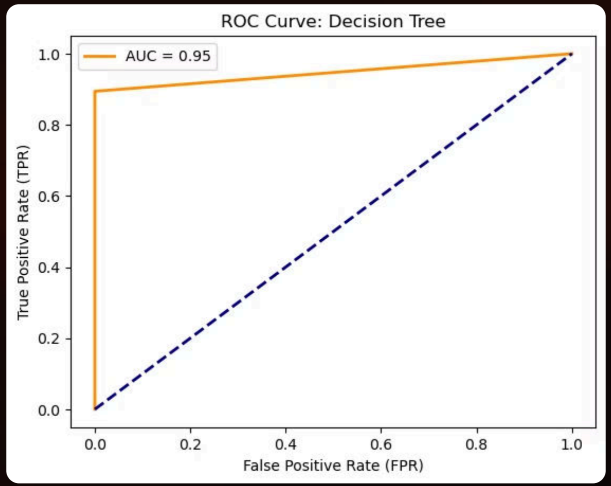
Made with Gamma

Baseline Models

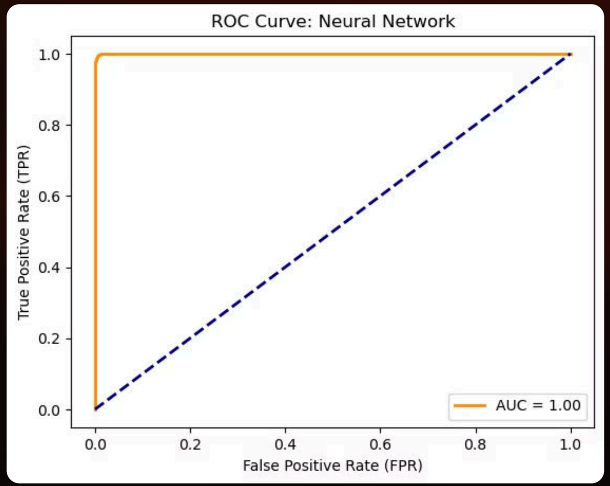
Initial baseline models were trained and tested. These models serve as a starting point for further improvements.



Logistic Regression



Decision Tree



Neural Network

Model Type	Accuracy	F1 Score
Logistic Regression	99.89%	0.9981
Decision Tree	95.75%	0.92.94
Neural Network	99.46%	0.9911

Next Steps

The project will continue to refine models and explore new approaches. Future work will focus on improving match quality and player experience.

1

Feature Engineering

Develop new features to capture more nuanced aspects of matchmaking.

2

Model Refinement

Improve existing models with additional features based on initial results.

3

Advanced Algorithms

Explore sophisticated architectures and ensemble modelling for better predictions.

4

Player Behaviour

Include chat sentiment analysis and other behavioural patterns to improve matchmaking.