

Team Evolution and Dynamics in Online Multiplayer Games

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A Counter-Strike character in tactical gear, including a helmet, balaclava, and vest with "POLIZEI" and a German flag patch, holding a handgun. The background is a dark, smoky environment.

New Game
Find Servers
Options
Quit

COUNTERSTRIKE



Motivation

Esports is a booming multi-billion-dollars industry where millions of players and viewers actively play and watch games everyday.

Gaming community, especially games with teamwork, is a fruitful environment to explore and analyze some of the real-world collaborative phenomena.

Insight to whether a team performance changes when a player(s) switch teams elucidates about the human collaboration and competition and aid in decision making for owners and coaches.




Counter Strike: Global Offense is a first-person shooter game with two teams (Counter-terrorists vs Terrorists) consist of 5 players each to compete in a best-of-30 match.

Champion at EMS One Katowice 2014

	K	A	D	ADR	3k	4k	5k	HS%	DBJ
1st	13	2	9	10.4	2	-	-	61%	2
2nd	3	-	-	3.8	1	-	-	100%	-

FAMAS



A professional CS:GO player is shown in a competitive environment, wearing a headset and a white jersey with 'G2A HYPER' and '2015' logos. He is seated at a desk with a computer monitor displaying a game, a keyboard, and a mouse. A large, professional microphone is positioned in front of him. In the background, a large, brightly lit arena is filled with a cheering crowd, and another player is visible standing nearby. The scene is illuminated with vibrant blue and purple stage lights.

The professional CS:GO scene hosts tournaments year-round with prize pool for teams from around the world to compete for.

CS:GO Major Championships have prize pools > \$1,000,000



Problem

This project aims to study the changes in team dynamics when a player transfer teams in Counter Strike: Global Offensive (CS:GO).

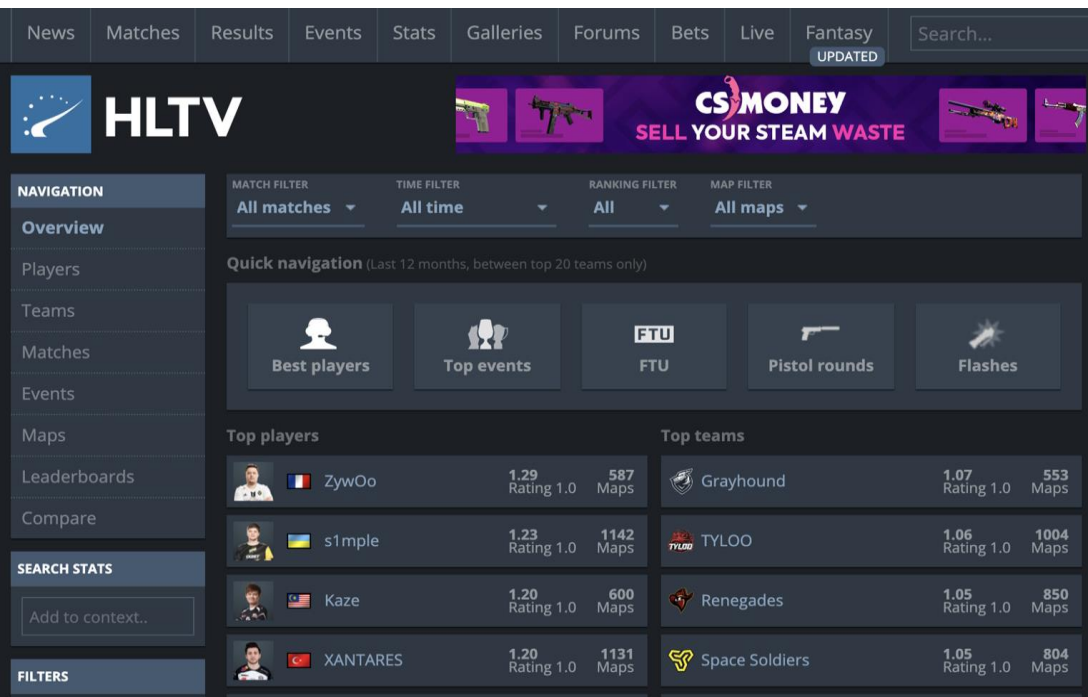
First, we will need a complete data collection on CS:GO statistics.

Our goal is to build models to explain the following questions:













- What is the effect on a **player** after changing the team?
- How does player transfer affects the **team** performance?

Data Source

HLTV.org is the most prominent website that keeps track of all major professional events in CS:GO.



The screenshot shows the HLTV website interface. At the top, there's a navigation bar with links: News, Matches, Results, Events, Stats, Galleries, Forums, Bets, Live, Fantasy, and a search bar. Below this is the HLTV logo and a banner for CS:GO MONEY. The main content area has a navigation sidebar on the left with links: Overview, Players, Teams, Matches, Events, Maps, Leaderboards, and Compare. The main content area features a 'Quick navigation' section with icons for Best players, Top events, FTU, Pistol rounds, and Flashes. Below this, there are two tables: 'Top players' and 'Top teams'.

Top players			Top teams		
	 ZywOo	1.29 Rating 1.0 587 Maps		Grayhound	1.07 Rating 1.0 553 Maps
	 s1mple	1.23 Rating 1.0 1142 Maps		TYLOO	1.06 Rating 1.0 1004 Maps
	 Kaze	1.20 Rating 1.0 600 Maps		Renegades	1.05 Rating 1.0 850 Maps
	 XANTARES	1.20 Rating 1.0 1131 Maps		Space Soldiers	1.05 Rating 1.0 804 Maps

Tabular data available:

- Players
- Teams
- Matches
- Events
- Maps



Our Data Schema



player_team_match	
id	int
player_id	int
team_id	int
match_id	int

teams	
id	int
name	varchar

players	
id	int
nick	varchar
full_name	varchar
age	int
nationality	varchar

matches	
id	int
team1_id	int
team2_id	int
team1_score	int
team2_score	int
event_id	int
date	timestamp

player_match_stats	
id	int
player_id	int
match_id	int
kills	int
flash_assists	int
deaths	int
KAST	float
KD_diff	int
ADR	float
FK_diff	int
rating	float
headshots	int
assists	int

events	
id	int
name	varchar
location	varchar
prize_pool	int
teams_no	int

player_stats	
id	int
player_id	int
Headshot %	float
K/D Ratio	float
Damage / Round	float
Grenade dmg / Round	float
Kills / round	float
Assists / round	float
Deaths / round	float
Saved by teammate / round	float
Saved teammates / round	float
weapons stats	varchar





Challenges in data collection

- ❖ Understanding of how the website is organized by the administrators of HLTV.org
 - E.g. Map ID vs Match ID (Each Match has several Maps and the Match results is the sum of all of the maps combined)
- ❖ Some of our first times in web scraping data and learning how to organize our data to avoid redundancy.
- ❖ Data cleaning and imputation on missing value for data
 - E.g. Calculate player tenure in various teams, or over the entire career



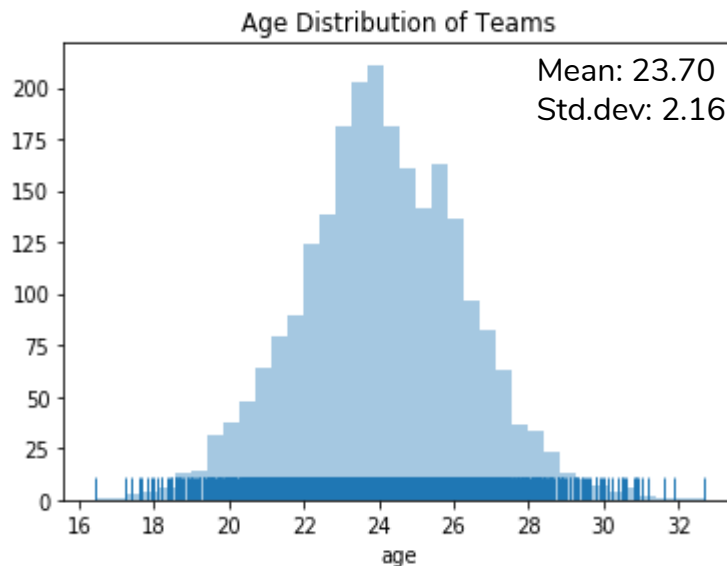
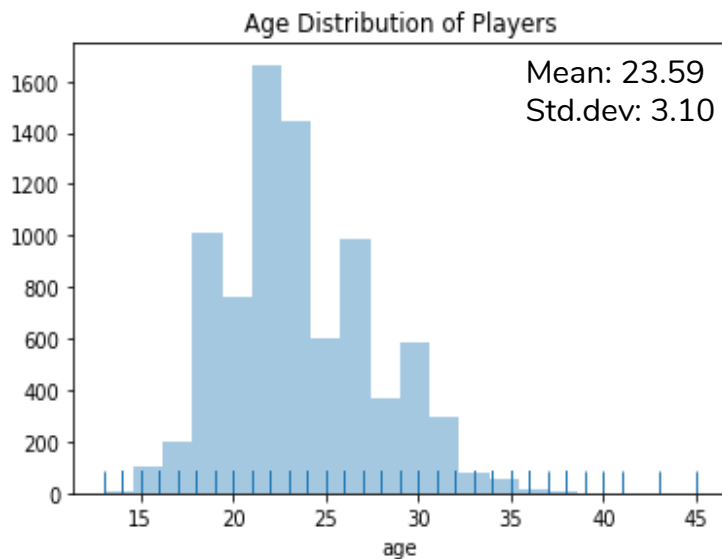
Approach

1. The data has been collected by web scraping using Python BeautifulSoup library 4.4.0 and Selenium.
2. A structured data schema has been created to organize the data sets and demonstrate relationships amongst data values.
3. We organized the data into dataframes and exported as csv files.
4. **We analyze the following:**
 - **Relation between player characteristics and player performance**
 - **Relation between team characteristics and team performance**
 - **What happens with player performance when switching the team**



Data statistics

Data Type	Count
Players	13706
Teams	4832
Matches	76450
Events	4051



Best Teams and Players of CS:GO



 **Natus
Vincere**



 **Astralis**



 **fnatic**



 **mousesports**



 **G2**

#1 ZYWOO
MATHIEU HERBAUT
19 YEARS

TEAMS
VITALITY

MVP AWARDS
cs summit 4
ESL One Cologne
EPICENTER

EVP AWARDS
ECS S7 Finals
DHL Masters Dallas
StarLadder Berlin
StarSeries S8
EM Chicago
EM Beijing

NOTABLE TEAM ACHIEVEMENTS
1st CS SUMMIT 4
ECS S7 FINALS
EPICENTER
2nd ESL ONE COLOGNE
DHL MASTERS DALLAS
3rd EM CHICAGO
EM BEIJING

PERSONAL STATS

	AVERAGE	
KPR	0.83	
SURVIVING	39.0%	
ADR	86.1	
IMPACT	1.40	
CONSISTENCY	74.5%	
RATING 2.0	1.30	

NOTABLE STATS

- 1.30 RATING (#1)
- 1.33 RATING IN BIG EVENT PLAYOFFS (#1)
- 86.1 DAMAGE PER ROUND (#1)
- 1.40 IMPACT RATING (#1)
- +95% K/D DIFFERENCE (#1)
- 0.83 KILLS PER ROUND (#2)
- 0.14 OPENING KILLS PER ROUND (#2)
- 61.3% OPENING DUELS WON (#5)
- 21.0% ROUNDS WITH A MULTI-KILL (#2)
- 74.5% KAST (#6)
- 61.1% SITUATIONS WON (#6)
- 1.21 T-SIDE RATING (#3)
- 1.30 CT-SIDE RATING (#1)
- 83.6% OF MAPS WITH 1.00+ RATING (#2)

#2 S1MPLE
ALEKSANDR KOSTYLIEV
22 YEARS

TEAMS
NATUS VINCERE

MVP AWARDS
StarSeries S7

EVP AWARDS
IEM Katowice
DHL Masters Dallas
EPICENTER

NOTABLE TEAM ACHIEVEMENTS
1st STARSERIES S7
2nd IEM KATOWICE
ESL ONE COLOGNE
DHL MASTERS DALLAS
BLAST COPENHAGEN
EPL S10 FINALS

PERSONAL STATS

	AVERAGE	
KPR	0.84	
SURVIVING	41.0%	
ADR	84.2	
IMPACT	1.33	
CONSISTENCY	74.6%	
RATING 2.0	1.29	

NOTABLE STATS

- 1.29 RATING (#2)
- 0.84 KILLS PER ROUND (#1)
- 84.2 DAMAGE PER ROUND (#4)
- 0.59 DEATHS PER ROUND (#5)
- 1.33 IMPACT RATING (#1)
- 74.6% KAST (#5)
- +80% K/D DIFFERENCE (#2)
- 0.13 OPENING KILLS PER ROUND (#8)
- 1.23 T-SIDE RATING (#1)
- 1.35 CT-SIDE RATING (#2)
- 22.0% ROUNDS WITH A MULTI-KILL (#1)
- 64.3% OPENING DUELS WON (#1)
- 86.7% OF MAPS WITH 1.00+ RATING (#1)
- 1.24 RATING IN BIG EVENT PLAYOFFS (#2)



Younger players play better

Linear Regression: Player Age vs Player Performance

- Older players have less kills per match (-0.0768)
- Older players have lower Kill-to-Death ratio (-0.0024)
- Older players have lower damage per round (-0.2067)
- Older players have fewer kills per round (-0.0025)
- $p < 0.0001$

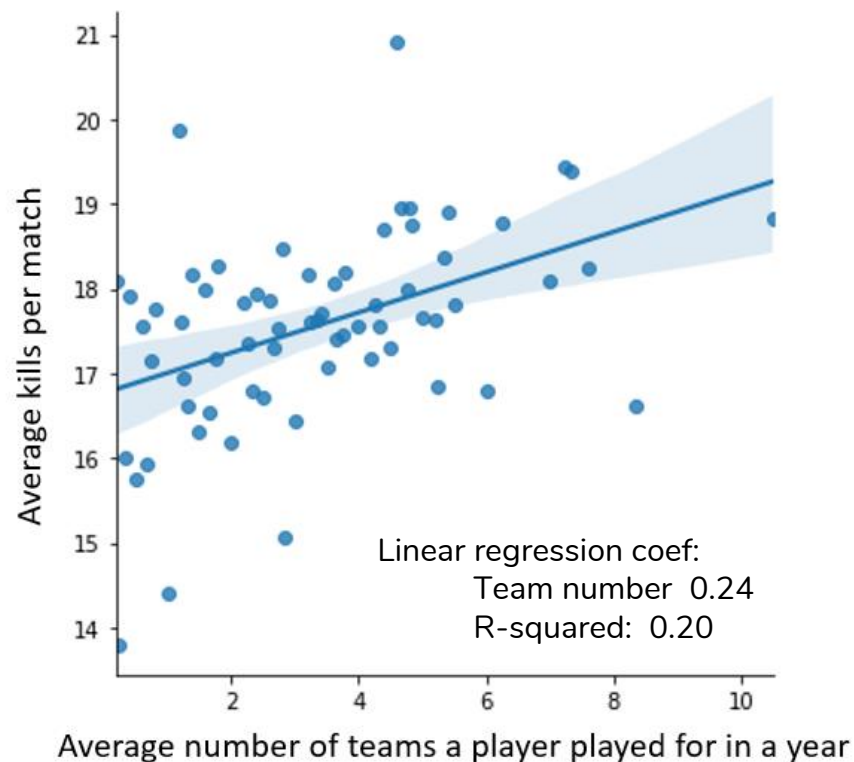
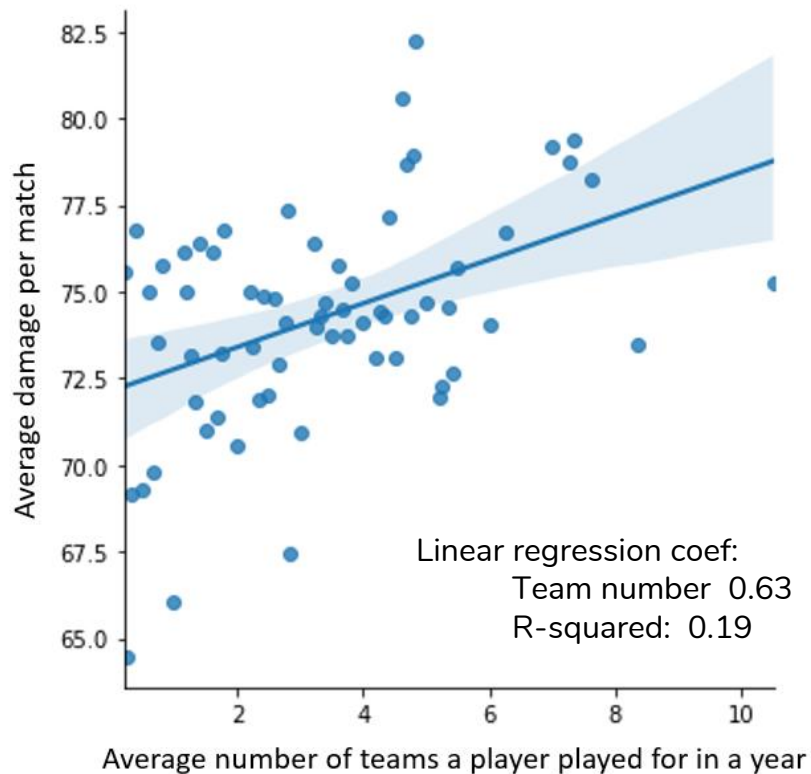


Players improve with the experience

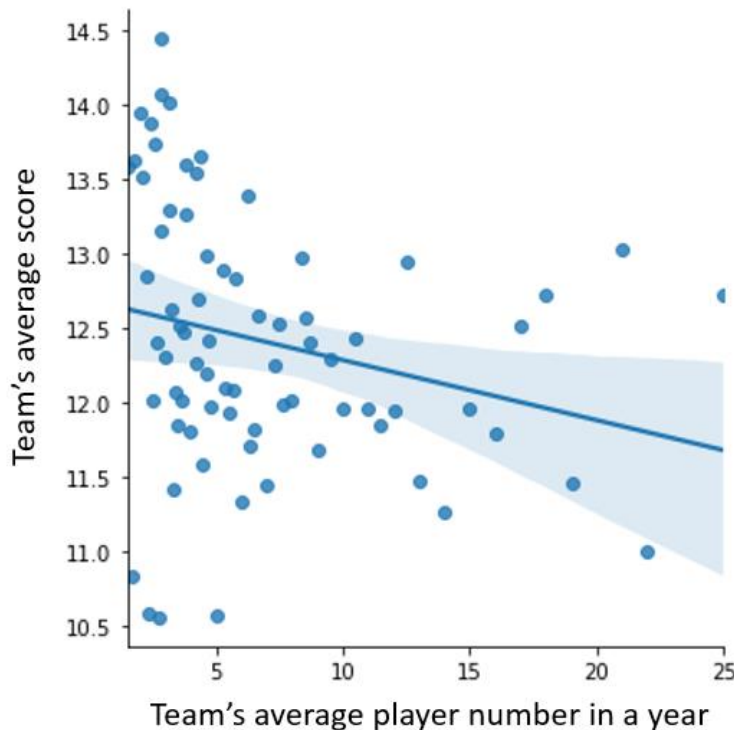
Linear regression: Player Tenure vs Player Performance

- More kills per day (0.0014)
- More damage per round (0.0016)
- More kills per round ($2.28e-05$)
- Similar kill/death ratio ($5.992e-05$)
- Similar headshot ratio (-0.0005)

Good players change teams often



Good teams are more stable - do not change players often





Change team does not affect player performance

For each player that played in at least 2 teams, we calculate the performance before and after the change, and compare it:

The average kills before change a team: 16.38

The average kills after change a team: 16.34



Questions?

