ECE 1786
Creative Applications of Natural Language Processing

Project Final Report

HoopScout

Word Count : 1979

Penalty : 0%

Introduction

In competitive basketball, developing game strategies against opposing teams and players is critical to success. This requires analyzing large volumes of player information and game statistics to identify key insights. However, with games happening almost daily, meeting the need for quick strategy development is challenging due to the tight time constraints.

To address this challenge, we propose a system using a Large Language Model (LLM) multi-agent architecture to automate pre-game report generation based on player information and the most recent game statistics available. These reports will provide actionable insights to help teams evaluate opposing players and devise strategies.
LLM multi-agent systems are suited for this task due to their ability to process dynamic datasets, read text, analyze player profile information to capture patterns, and generate actionable insights with natural language understanding.

Illustration

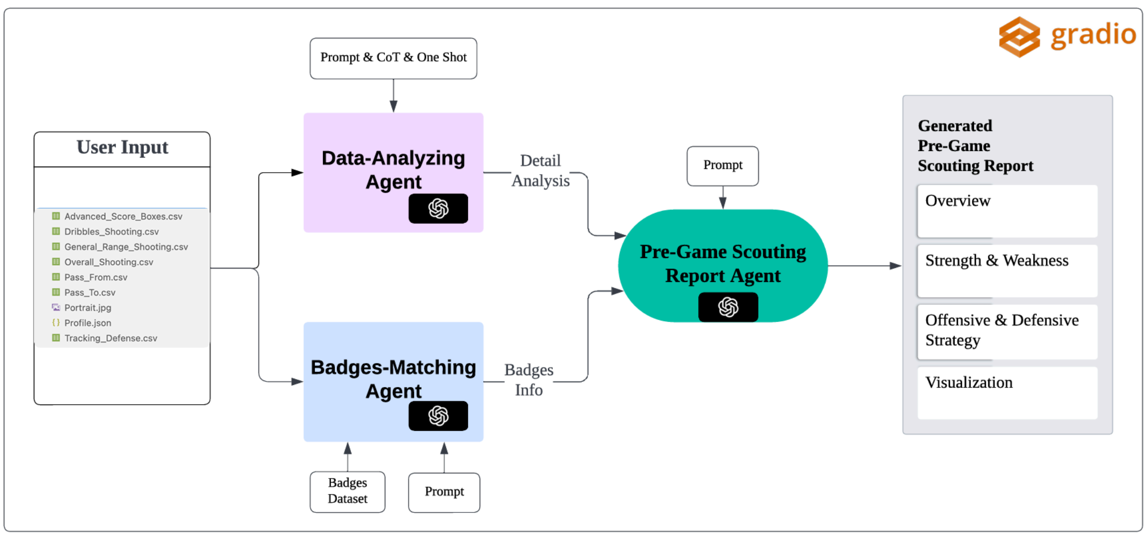

Figure 1: Architecture of the multi-agent system

Background and Related Work

Since LLMs don't require traditional training, prompt engineering is key to achieving detailed, accurate responses. G. Marvin et al. [1] demonstrate how techniques like role prompting, emotion prompting, and chain of thought can improve accuracy, coherence, and relevance in zero- and few-shot settings.

Similarly, M. Sudarshan [2] explores multi-agent workflows for generating structured, accurate reports. In their architecture, multiple zero-shot prompted letters are generated, evaluated by a reflection agent for accuracy and readability, and then refined. This research highlights the importance of domain knowledge, critical thinking, and iterative improvement in designing effective prompts.

Data and Data Processing

For generating detailed scouting reports, the system would need access to both regular and advanced statistics. We sourced our data from *www.NBA.com/stats*, which is the official website for detailed and up-to-date statistics suitable for our task.

For each player, we collected and classified data into 9 files, including 1 json file of the player's profile (shown below), 7 csv files with different aspects of the player's performance in the latest matches, and a player portrait picture is also used to complete the scouting report.

The csv files consist of:

- Advanced box scores (points(PTS), 3-point percentage(3P%), rebounds(REB), assists(AST), etc.)
- Shooting stats (Overall field goal frequency(FREQ%), field goal across different ranges, dribbles, etc.)
- Passing stats (Frequency made(FREQ M%), frequency received(FREQ R%), etc.)
- Defense stats (Defended field goals (DFGM), frequency (FREQ%), percentage (FG%), etc.)

Note that the player portrait was inserted into the report in the final stage for visual aid - it was not used in analyzing or decision-making.

As for data for the team-level report, a team roster background file (csv) and the team logo are collected to replace player profile and portrait, while the other stats are similar.

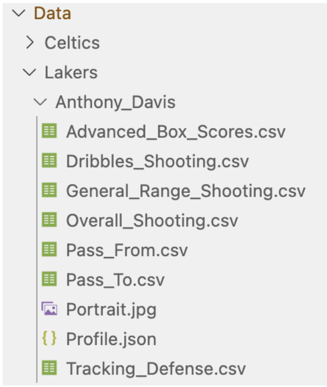

Figure 2: Data for Each Player

```json
{
    "name": "Anthony Davis",
    "number": 3,
    "team": "Los Angeles Lakers",
    "position": ["Power Forward", "Center"],
    "height": {
        "feet": 6,
        "inches": 10,
        "meters": 2.08
    },
    "weight": {
        "pounds": 253,
        "kilograms": 115
    }
}
```

Figure 3: Player Profile

MATCH UP	W/L	MIN	PTS	FGM	FGA	FG%	3PM	3PA	3P%	FTM	FTA	FT%	OREB	DREB	REB	AST	STL	BLK	TOV	PF	+/-
Nov 27, 2024 - LAL @ SAS	W	35:07	19	8	14	57.1	0	2	0.0	3	3	100	4	10	14	7	1	0	1	2	16
Nov 26, 2024 - LAL @ PHX	L	34:43	25	10	19	52.6	0	2	0.0	5	7	71.4	2	13	15	5	1	4	3	3	-24
Nov 23, 2024 - LAL vs. DEN	L	35:24	14	6	19	31.6	0	2	0.0	2	3	66.7	3	7	10	3	3	2	1	2	-26
Nov 21, 2024 - LAL vs. ORL	L	37:46	39	14	22	63.6	1	1	100	10	13	76.9	4	5	9	2	0	3	3	4	0
Nov 19, 2024 - LAL vs. UTA	W	33:52	26	10	15	66.7	0	1	0.0	6	10	60.0	4	10	14	6	2	0	0	3	4
Nov 16, 2024 - LAL @ NOP	W	37:14	31	12	20	60.0	2	4	50.0	5	7	71.4	3	11	14	1	2	1	2	3	2
Nov 15, 2024 - LAL @ SAS	W	36:10	40	14	26	53.8	2	4	50.0	10	12	83.3	5	7	12	2	1	2	2	1	12
Nov 13, 2024 - LAL vs. MEM	W	32:00	21	6	16	37.5	2	3	66.7	7	8	87.5	2	12	14	3	0	3	3	5	-6
Nov 10, 2024 - LAL vs. TOR	W	25:53	22	6	8	75.0	2	2	100	8	10	80.0	1	3	4	3	1	2	0	1	-3
Nov 08, 2024 - LAL vs. PHI	W	35:30	31	11	20	55.0	2	3	66.7	7	8	87.5	3	6	9	1	0	4	3	2	20
Nov 04, 2024 - LAL @ DET	L	39:00	37	13	23	56.5	0	4	0.0	11	14	78.6	1	8	9	4	0	0	3	2	-1
Nov 01, 2024 - LAL @ TOR	W	35:42	38	14	20	70.0	0	0	0.0	10	11	90.9	1	10	11	2	3	2	3	0	7
Oct 30, 2024 - LAL @ CLE	L	31:20	22	9	17	52.9	0	1	0.0	4	8	50.0	1	12	13	2	2	0	4	1	-18
Oct 28, 2024 - LAL @ PHX	L	35:30	29	12	24	50.0	0	2	0.0	5	6	83.3	5	10	15	3	1	3	3	1	14
Oct 26, 2024 - LAL vs. SAC	W	37:45	31	10	15	66.7	1	2	50.0	10	13	76.9	3	6	9	2	3	2	2	1	-22
Oct 25, 2024 - LAL vs. PHX	W	37:30	35	11	18	61.1	0	0	0.0	13	17	76.5	1	7	8	4	1	2	1	2	4
Oct 22, 2024 - LAL vs. MIN	W	37:35	36	11	23	47.8	1	3	33.3	13	15	86.7	3	13	16	4	1	3	1	1	1

Figure 4: Example CSV File

Architecture and Software

As illustrated in Part 2's flowchart, our system employs a multi-agent architecture integrated within a Gradio interface, providing an user-friendly platform. Users input a player's basic profile and advanced performance statistics from recent games. The system then relies on specialized agents—one focused on analyzing performance data, another on awarding badges based on predefined criteria. Finally, these results are consolidated to produce a comprehensive pre-game scouting report that aids strategic decision-making and deepens understanding of opposing players' strengths and tendencies.

The following sections provide explanations of each LLM agent's specific roles and the techniques employed to generate desired outputs.

Data-Analyzing Agent
The Data-Analyzing Agent serves as the main writer of the scouting report. By leveraging advanced prompt engineering techniques, the agent excels in identifying insightful patterns from the provided data, generating a detailed player analysis.

- *Role prompting*: A prompting technique that sets context and range to the agent to understand the type of perspectives and depth of response it should adopt, better utilizing existing capabilities and knowledge of the GPT4o model.
  Example prompt: "you are a professional NBA scout and data analyst, you are really good at extracting and identifying insightful patterns and information from player's numerical stats."

- *Chain of Thoughts*: Building on role prompting, CoT breaks down the task into manageable steps, allowing the agent to follow a logical reasoning sequence.
  Example CoT Prompts:
  - "Look at shooting efficiency (FG%, 3P%, eFG%) for offensive insights.
  - Negative defensive field goal percentage (DFG%) should determine strong defensive ability.
  - "High usage rate with high efficiency and high PPG = central player in the offense."

- *One Shot Prompting*: By providing a single example of input data and corresponding analysis within the prompt, this method demonstrates the correct approach and format, enhancing output quality and reducing ambiguity.
  Example Content:
  - "With 2.8 assists per game, Davis demonstrates solid vision for a big man."
  - "Davis has strong passing connections with LeBron James 14.3 passes to and 16.5 passes from per game, showcasing strong chemistry in pick-and-roll and transition plays."

Badge-Matching Agent
This agent emulates a basketball video game's badging system, assigning up to six badges to a player if specific conditions are met. For instance, a player with a Catch and Shoot FG% ≥ 45%, Catch and Shoot 3P% ≥ 38%, Frequency (Freq%) ≥ 40%, Points from Catch and Shoot ≥ 6 PPG qualifies for the Catch & Shoot badge, as depicted in Figure 2. The corresponding badge icon is then displayed in the player's report. These badges provide a visual representation of complex data, each symbolizing unique attributes of the player.

We utilized an LLM to implement badge matching. Though hardcoded rule-based algorithms might achieve better accuracy and efficiency, player data formats often vary across organizations. The LLM agent effectively identifies relevant statistics when provided with well-crafted prompts, even when data formats differ among players. However, if we can preprocess and standardize our data formats, a hardcoded rule-based algorithm would be recommended. In this project, We also developed a rule-based function for player badge matching.

Pre-Game Scouting Report Agent
By consolidating the outputs from the previous agents, this agent restructures and integrates the player's badge information and performance analysis into the final pre-game scouting report. Utilizing one-shot prompting, the agent produces a more well-structured report.

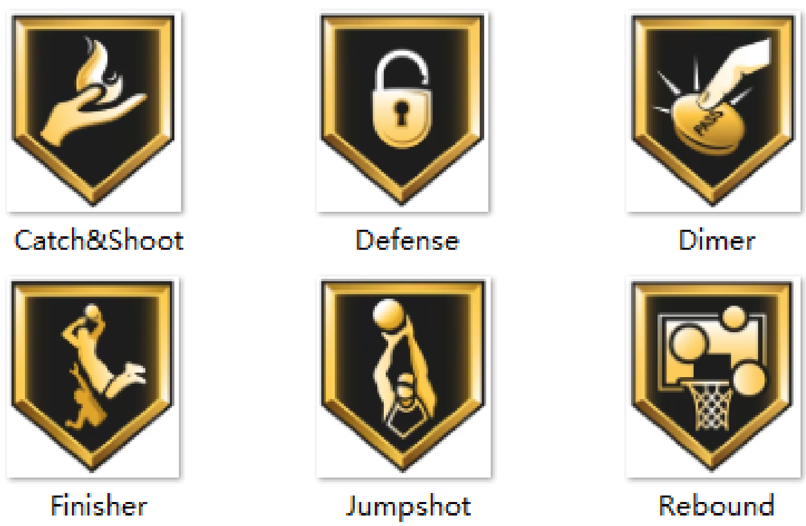

Figure 5: Type of Badges

In addition, a Team Report Agent is developed to provide high-level overviews of team performances. It could replace the previous report agent to generate team-level reports, taking in the stats of a whole team and its roster information, while removing the badge-matching functionality for simplicity.

Baseline Model
A good pre-game scouting report delves into player statistics and performance trends, providing actionable insights that are both accurate and relevant for strategic planning. The report should be structured into sections such as player overview, strengths, weaknesses, and offensive/defensive strategies against the player. Incorporating visual

elements like player portraits and badge icons enhances the overall quality and readability. Additionally, the report must be highly readable and easy to understand, enabling players and coaches to quickly grasp essential information about the opposing team during pre-game preparations without requiring extensive time to digest the content.

Since professional pre-game scouting reports are not publicly accessible, we rely on individuals with existing NBA knowledge for evaluation. A grading rubric is developed that includes criteria mentioned before. (See Figure 3.) Additionally, an automated grader is used, featuring a rule-based function to verify player badge matching and the Flesch-Kincaid Grade Level metric to evaluate readability. This readability measure, based on syllables per word and words per sentence, translates into a U.S. school grade level. Considering the educational background of NBA players, we aim for a Flesch-Kincaid level of 9 to 11.

Quantitative Results

To evaluate the performance of the multi-agent system. We used a combination of automated and human-evaluated quantitative metrics aligned with the rubric as shown in Figure 6.

Using zero-shot prompting, the system achieved an average score of 72.4 across 18 reports. By incorporating one-shot prompting, which provided the model with a relevant example, the average performance improved to 88.2. This demonstrates that the model benefits from contextual guidance, which helps refine its response and better aligns with the requirements.

The badge-matching scores were notably low. Badge matching, which evaluates the alignment of player attributes with predefined rules, depends on precise numerical reasoning. Without detailed and explicit prompt guidance, the LLM's performance in this task was suboptimal. After refining the prompts, the accuracy showed some improvement, demonstrating the importance of clear guidance. However, based on the observed result, it is clear that LLM is not the optimal solution for complex numerical operations. On a positive note, the Flesch-Kincaid readability score exceeded the targeted level of 9-10, reflecting clarity.

Relevance and depth of insights, including strengths, weaknesses, and strategic suggestions are evaluated by humans. The system consistently performed well in these categories, particularly when guided by one-shot prompting.

Category	Criteria	Points
1. Accuracy & Readibility	**Accuracy (15 points):** Are generated statistics align with the input data?	/15
	Badges Matching (15 points): Are badges correctly matches with the player?	/15
	Readability (15 points): Evaluate the readibility based on Flesch Kincaid Grade	/15
	Total for Accuracy & Readibility	**/45**
2. Overview	**Relevance (10 points):** Does the overview summarize the player's key contributions accurately?	/5
	Total for Overview	**/5**
3. Strengths & Weaknesses	**Depth (10 points):** Are strengths/weaknesses insightful and supported by data?	/10
	Relevance (10 points): Are they relevant to the player's recent performance?	/10
	Total for Strengths & Weaknesses	**/20**
4. Strategic Suggestions	**Offensive Strategy (10 points):** Are suggestions actionable and aligned with player weaknesses?	/10
	Defensive Strategy (10 points): Are suggestions actionable and aligned with player strengths?	/10
	Total for Strategic Suggestions	**/20**
5. Structure	**Aesthetic Quality (5 points):** Is the report visually appealing, professional and structured?	/5
	Consistency (5 points): Are images, stats, and analysis cohesive throughout the report?	/5
	Structure	**/10**

Figure 6: Rubric for System Performance Evaluation

Qualitative Results

The following content is extracted from the generated report on Austin Reaves:

- "Efficient scoring within 10 feet at a 56.5% conversion, adaptable in many offensive roles."
- "Allows 42.9% opponent conversion on three-point attempts, posing a potential defensive liability."
- "His offensive threat is notable, marked by a recent 26-point game, and he plays a vital role in the team's dynamics alongside LeBron and Anthony Davis."
- "Consider targeted fouling in tight games due to his 62.63 FT%."

The claims in the report are both reasonable and well-supported by the provided statistics. Beyond the numbers, the report effectively identifies patterns and actionable insights. For instance, analyzing the player's 62.63 FT% leads to the recommendation of intentional fouling in close games, which is both logical and strategic. Furthermore, the qualitative depth of the generated report largely depends on the prompts provided to the agent. A detailed and professional guide prompt can significantly enhance the quality and depth of its analysis.

Discussion and Learnings

The model effectively identifies patterns and analyzes data, yet opportunities exist to enhance strategic detail and overall reliability. The final pre-game report excels visually, presenting a clean layout with a player portrait, a concise stats table, and badge icons. This format allows readers to quickly grasp the player's identity and advantages. Structurally, the report is well-organized—sections on overview, strengths, weaknesses, and offensive/defensive strategies are all clearly separated and use bullet points for better readability. The statistics are current and accurately highlight the player's qualities. However, the recommended strategies remain somewhat generic and could benefit from more specific, actionable steps. Additionally, comparing the player's performance to league averages would provide richer context.

As for team-level reports, the output follows the same layout, correctly identifies the recent trends of the team and its standout players, and is decent in providing a quick overview. But it lacks accurate stats and comparisons to back up the conclusion, and the strategies also need improvement.

For future projects, several key improvements are planned. First, we will further refine the multi-agent framework to minimize redundancy and handle more complex tasks, as current results can be achieved with a single agent and prompt. Second, we will enhance prompt detail so the agents produce more nuanced and credible responses. Lastly, we will preprocess collected data before feeding it to GPT, focusing its attention on analysis and reducing potential numerical errors. These efforts aim to create more insightful, actionable, and reliable scouting reports.

Individual Contributions

Weiran Wang

- Developed badge-matching agent, data-analysing agent, pre-game report generation agent with zero shot/one shot.
- Developed function to calculate player's average stats, avoiding LLM doing complex number operations.
- Developed evaluation function to check player's badges matching, and the readability evaluation.
- Wrote Gradio implementation of the user-facing side of the project.

Long Zhuang

- Collected 6 player input data
- Generated player reports
- Resolved image rendering issues
- Developed rubric for evaluation
- Revised one shot to zero shot

Amos Zhou

- Collected 6 players data for Lakers
- Modified and improved Gradio

- Developed and tested on single-prompt and single agent without data input
- Improved pre game report agent

Yue Chen

- Collected 6 players data
- Collected team data for Celtics
- Developed team-report agent and related data processing
- Developed Gradio implementation for team-report generation

References

[1] G. Marvin, N. Hellen, D. Jjingo, and J. Nakatumba-Nabende, “Prompt engineering in large language models,” SpringerLink, https://link.springer.com/chapter/10.1007/978-981-99-7962-2_30 (accessed Nov. 4, 2024).

[2] M. Sudarshan1 et al., Agentic LLM workflows for Generating Patient-friendly medical reports, https://arxiv.org/html/2408.01112v2 (accessed Nov. 4, 2024).

[3] "Flesch Reading Ease and Flesch-Kincaid Grade Level." Readable, readable.com/readability/flesch-reading-ease-flesch-kincaid-grade-level/. Accessed 18 Nov. 2024.

[4] M. Sudarshan1 et al., Agentic LLM workflows for Generating Patient-friendly medical reports, https://arxiv.org/html/2408.01112v2 (accessed Nov. 4, 2024).

Permissions

Name	**Permission**	**Answer**
Weiran Wang	Permission to post video	yes
	Permission to post final report	yes
	Permission to post source code	yes
Amos Zhou	Permission to post video	yes
	Permission to post final report	yes
	Permission to post source code	yes
Angela Zhuang	Permission to post video	yes
	Permission to post final report	yes
	Permission to post source code	yes
Yue Chen	Permission to post video	yes
	Permission to post final report	yes
	Permission to post source code	yes

Appendix

Pre-Game Scouting Report

Austin Reaves

Los Angeles Lakers | #15 | Guard | 6'5"| 197 lb

PPG	RPG	APG	SPG	BPG	FG%	3P%	FT%
17.44	3.56	5.31	1.12	0.25	44.23%	35.21%	62.63%

Overview:

Austin Reaves is an integral part of the Lakers' backcourt, offering substantial contributions in scoring and playmaking. Despite his capabilities, he faces inconsistent shooting efficiency and occasional defensive lapses. His offensive threat is notable, marked by a recent 26-point game, and he plays a vital role in the team's dynamics with LeBron and Anthony Davis.

Key Strengths:

- **Playmaking:** Facilitates offense effectively with **5.31 assists per game**, creating opportunities for teammates.
- **Perimeter Shooting:** Solid from the three-point line, shooting **35.21%** overall; particularly strong in catch-and-shoot plays.
- **Versatility in Offense:** Efficient scoring within **10 feet** at a **56.5% conversion**, adaptable in many offensive roles.

Key Weaknesses:

- **Shooting Consistency:** Faces fluctuations in FG%, with **44.23% overall**, impacting his scoring reliability.
- **Free Throw Inefficiency: 62.63% FT%** indicates vulnerability during crucial free throw moments.
- **Defensive Challenges:** Allows **42.9% opponent conversion** on three-point attempts, posing a potential defensive liability.

Offensive Strategy:

- **Utilize Screen-and-Roll:** Leverage pick-and-roll to expose defensive gaps and force Reaves into less advantageous matchups.
- **Engage Quick, Agile Guards:** Employ fast-paced movements and cuts to test his defense, aiming to exploit moderate defensive metrics.

Defensive Strategy:

- **Disrupt Catch-and-Shoot:** Close out aggressively to limit his effectiveness from three-point range.
- **Exploit Free Throw Weakness:** Consider targeted fouling in tight games due to his **62.63% FT%**.

Appendix 1. Generated Pre-Game Scouting Report

			FIELD GOALS					2 POINT FIELD GOALS				3 POINT FIELD GOALS			
OVERALL	GP	G	FREQ%	FGM	FGA	FG%	EFG%	FREQ%	2FGM	2FGA	2FG%	FREQ%	3PM	3PA	3P%
Overall	17	17	100	10.4	18.8	55.5	57.5	88.7	9.7	16.6	58.0	11.3	0.8	2.1	36.1

			FIELD GOALS					2 POINT FIELD GOALS				3 POINT FIELD GOALS			
GENERAL RANGE	GP	G	FREQ%	FGM	FGA	FG%	EFG%	FREQ%	2FGM	2FGA	2FG%	FREQ%	3PM	3PA	3P%
Catch and Shoot	17	17	16.9	1.2	3.2	38.9	50.9	6.9	0.5	1.3	36.4	10.0	0.8	1.9	40.6
Pull Ups	17	16	14.4	0.8	2.7	30.4	30.4	13.5	0.8	2.5	32.6	0.9	0.0	0.2	0.0
Less than 10 ft	17	17	67.1	8.3	12.6	65.9	65.9	67.1	8.3	12.6	65.9	0.0	0.0	0.0	-
Other	17	4	1.6	0.1	0.3	20.0	20.0	1.3	0.1	0.2	25.0	0.3	0.0	0.1	0.0

			FIELD GOALS					2 POINT FIELD GOALS				3 POINT FIELD GOALS			
DRIBBLES	GP	G	FREQ%	FGM	FGA	FG%	EFG%	FREQ%	2FGM	2FGA	2FG%	FREQ%	3PM	3PA	3P%
0 Dribbles	17	17	53.3	6.3	10.0	62.9	66.8	42.9	5.5	8.1	68.6	10.3	0.8	1.9	39.4
1 Dribble	17	16	16.0	1.3	3.0	43.1	43.1	15.0	1.3	2.8	45.8	0.9	0.0	0.2	0.0
2 Dribbles	17	15	13.5	1.3	2.5	51.2	51.2	13.5	1.3	2.5	51.2	0.0	0.0	0.0	-
3-6 Dribbles	17	14	11.9	0.9	2.2	42.1	42.1	11.9	0.9	2.2	42.1	0.0	0.0	0.0	-
7+ Dribbles	17	12	5.3	0.6	1.0	58.8	58.8	5.3	0.6	1.0	58.8	0.0	0.0	0.0	-

Appendix 2. CSV of Shooting Stats

					FIELD GOALS			2 POINT FIELD GOALS			3 POINT FIELD GOALS		
PASS TO	TEAM	FREQ M%	PASS	AST	FGM	FGA	FG%	2FGM	2FGA	2FG%	3FGM	3FGA	3FG%
James, Bronny	LAL	0.1	0.1	0.0	0.0	0.0	-	0.0	0.0	-	0.0	0.0	-
Knecht, Dalton	LAL	4.4	2.3	0.3	0.5	1.3	40.9	0.5	0.9	53.3	0.1	0.4	14.3
Christie, Max	LAL	2.3	1.2	0.1	0.2	0.4	42.9	0.2	0.4	42.9	0.0	0.0	-
Reaves, Austin	LAL	32.0	16.6	0.8	1.4	3.9	36.4	0.8	1.8	43.3	0.7	2.1	30.6
Reddish, Cam	LAL	2.4	1.2	0.1	0.1	0.1	100	0.0	0.0	-	0.1	0.1	100
Vincent, Gabe	LAL	4.0	2.1	0.0	0.0	0.1	0.0	0.0	0.0	-	0.0	0.1	0.0
Hachimura, Rui	LAL	4.0	2.1	0.3	0.3	0.7	50.0	0.2	0.3	50.0	0.2	0.3	50.0
Russell, D'Angelo	LAL	19.0	9.8	0.3	0.6	1.8	33.3	0.5	1.2	38.1	0.1	0.5	22.2
James, LeBron	LAL	31.8	16.5	1.2	2.0	4.1	48.6	1.3	2.9	44.0	0.7	1.2	60.0

					FIELD GOALS			2 POINT FIELD GOALS			3 POINT FIELD GOALS		
PASS FROM	TEAM	FREQ R%	PASS	AST	FGM	FGA	FG%	2FGM	2FGA	2FG%	3FGM	3FGA	3FG%
Traore, Armel	LAL	0.1	0.1	0.0	0.0	0.0	-	0.0	0.0	-	0.0	0.0	-
Knecht, Dalton	LAL	4.9	2.5	0.4	0.6	0.9	66.7	0.5	0.7	66.7	0.1	0.2	66.7
Christie, Max	LAL	4.1	2.1	0.2	0.6	0.9	62.5	0.6	0.9	62.5	0.0	0.0	-
Reaves, Austin	LAL	32.1	16.2	1.4	2.1	5.5	37.2	1.9	5.1	36.8	0.2	0.4	42.9
Hayes, Jaxson	LAL	0.3	0.2	0.0	0.0	0.2	0.0	0.0	0.2	0.0	0.0	0.0	-
Reddish, Cam	LAL	2.8	1.4	0.0	0.0	0.2	0.0	0.0	0.2	0.0	0.0	0.0	-
Vincent, Gabe	LAL	4.4	2.2	0.1	0.2	0.7	33.3	0.2	0.7	36.4	0.0	0.1	0.0
Hachimura, Rui	LAL	3.5	1.8	0.2	0.3	0.8	42.9	0.3	0.8	42.9	0.0	0.0	-
Russell, D'Angelo	LAL	20.0	10.1	1.3	1.6	3.8	42.2	1.5	3.3	44.6	0.1	0.5	25.0
James, LeBron	LAL	27.8	14.1	3.1	3.2	5.8	54.5	2.8	4.8	59.3	0.3	1.1	33.3

Appendix 3. CSV of Passing Stats

DEFENSE CATEGORY	GP	G	DFGM	DFGA	DFG%	FREQ%	FG%	DIFF%
Overall	17	17	7.9	18.0	44.1	100	49.0	-4.9
3 Pointers	17	17	1.8	6.2	29.2	34.6	35.9	-6.7
2 Pointers	17	17	6.1	11.8	52.0	65.4	56.6	-4.6
Less Than 6 Ft	17	17	4.2	7.2	58.2	39.9	66.1	-7.9
Less Than 10 Ft	17	17	4.9	8.8	56.4	48.7	61.5	-5.1
Greater Than 15 Ft	17	17	2.2	7.7	29.0	42.8	37.2	-8.2

Appendix 4. CSV of Defense Stats

Pre-Game Scouting Report

Boston Celtics

Established NBA team renowned for defensive prowess and strong firepower from the perimeter.

PPG	RPG	APG	SPG	BPG	FG%	3P%	FT%
120.2	42.8	26.0	7.4	5.4	46.1	37.5	80.9

Overview:

The Boston Celtics are on a winning streak, with a robust record of 15-3. They have bolstered their roster with seasoned players like Jayson Tatum and Jrue Holiday contributing significantly in scoring and defense, complemented by Jaylen Brown's efficiency on the wings. Recent games show a dominant performance in both offense and defense.

Key Strengths:

- Outstanding three-point shooting and perimeter playmaking.
- Strong defensive guard play, led by Jrue Holiday and Derrick White.
- Consistent scoring from multiple players, leading to a high points-per-game average.

Key Weaknesses:

- Susceptibility to turnovers, averaging 11.7 per game.
- Potential vulnerabilities in the paint against teams with dominant inside presence.
- Dependence on perimeter shooting can lead to shooting slumps.

Offensive Strategy:

- Exploit their susceptibility to interior defense by attacking the paint aggressively.
- Capitalize on transition opportunities to pressure their ball handlers into turnovers.

Defensive Strategy:

- Defend the three-point line aggressively to limit their effective long-range shooting.
- Apply pressure to their primary ball handlers like Jayson Tatum and Jaylen Brown to increase turnover chances.

Appendix 5. Generated Team-Level Pre-Game Scouting Report