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Performance Analysis & Data Science (Seminar)

Two different studying tracks customised for students from

1. *Computer Science and DSAI (M.Sc. 7 ECTS)*
2. *Sports Science (M.Sc. High-Performance Sports, 5 ECTS)*

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[I30310 Performance Analysis and data-science](#)
[Chair for Sports Analytics, Saarland University](#)

Please use the following subject for any email-communication „*Seminar: I30310 Performance Analysis and data-science | [YOUR REQUEST]*" at pascal.bauer@uni-saarland.de

Course Summary

Performance Analysis & Data Science (PADS)				
Study Semester 4	**Cycle** Annually	**Duration** 1 Sem.	**Weekly Hrs** 2	**ECTS Pts.** 7 (CS, DSAI) / 5 (HPS)
Module Leader	Jun.-Prof. Dr. Pascal Bauer			
Admission Prerequisites	• **CS and DSAI students**: Knowledge in programming (Python or R) • **HPS students**: Statistics; Basic programming skills desirable			
Assessments	Multiple Choice-tests, Presentation, Hands-On Project, (Project Submission)			
Semester Workload	**CS and DSAI students (7 ECTS):** 210 hrs • In-Person Attendance: 25 hrs • Assignments/Projects: 185 hrs		**HPS students (5 ECTS):** 150 hrs • In-Person Attendance: 25 hrs • Assignments/Projects: 125 hrs	

**CS* Computer science, *HPS* High-Performance Sport

Course Summary

Performance Analysis & Data Science by Juni.-Prof. Dr. Pascal Bauer

This interdisciplinary course combines data science approaches with sport science knowledge. It is particularly aimed at students with a programming background who are interested in data analytics in high performance sport. For students from the CS department, a customised learning pathway will primarily focus on the advancing and extending performance metrics in real-world applications, including more sophisticated programming tasks and additional project work. Through lectures, presentations, and practice-oriented analytical projects, students examine and further develop established performance metrics across sports, such as Expected Goals and Strokes Gained with a focus on their practical relevance and application.

Requirements: For CS students, knowledge in programming (Python or R) is required. For HPS students, fundamental knowledge of statistics is required, and basic programming skills are highly desirable.

Capacity: 5–30

Course Prerequisites

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Prerequisite Skills

💻 **Programming Experience in Python or R**

📈 **Basics in Statistics (and Data Science)**

Mandatory
Recommended

Programme	Course Prerequisites	
M.Sc. Computer Science	Basics in Coding (i.e. Programming 1-2) *AND* Statistics *AND* Data-Science Practical Project (e.g. Bachelor's Thesis)	
M.Sc. Data Science and Artificial Intelligence	Basics in Coding (i.e. Programming 1-2) *AND* Statistics *AND* Data-Science Practical Project (e.g. Bachelor's Thesis)	
M.Sc. High Peformance Sports	Advanced Statistics	Programming & Data Analysis
Other Programs	Advanced Statistics Courses	Programming Courses

Course Summary—Learning Objectives

- Critically **evaluate physical, technical, and tactical performance** across sports and **understand established key performance indicators** across sports (e.g. Expected Goals, Strokes Gained, etc.)
- Critically **assess methods and metrics for quantifying performance** in sports
- Critically **discuss complex concepts of performance analysis** with practitioners
- **Describe application areas** (e.g., load management, scouting, game analysis) as well as **established professional fields and roles** in high-performance sport (e.g., Head of Performance, Data Scientist, Data Analyst, Video Analyst, Scout, etc.)
- With practical projects, students will learn to ***either***
  - **apply standard data-science methods** (e.g., clustering, classification, regression) to sports datasets using **programming languages (e.g., Python, R), *or***
  - **create web-based interface applications or BI-Dashboards**, ***or***
  - **conduct structured video analyses** (e.g. opponent analysis or scouting) using sports data

CS/DSAI students are required to accomplish a data-science-related project

Task Description

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Lecture

- Introduction to key research topics and standard datasets / data collection in sports
- Overview of state-of-the-art applications in sports performance analysis
- Multiple-choice tests after each seminar to test students' theoretical knowledge

Presentation

- Comprehend methods and metrics for quantifying performance in sports
- Discuss application areas of established performance indicators
- Discuss complex concepts of performance analysis with practitioners

Hands-On Project

- Build usable metrics, dashboards, and/or reports using ready-to-use data from elite sports
- Interdisciplinary and applied collaboration among students from different backgrounds
- Develop skills in presenting within a short time window

Project Submission
(for CS students taking 7 credits)

- Submit hands-on project in a concise and academic manner
- Train the ability to condense complex ideas, methodologies into standardized academic submissions
- Structured submission of the project (presentation, code, and report)

Task assignment & difficulty will match students' backgrounds, with CS students receiving more advanced coding tasks.

Semester Overview

Date	Topic	Presenter
16.10.2026	Performance Analysis & Data Science—Introduction & Topic Assignments	Pascal Bauer
23.10.2026	Introduction to Datasets, Reportings and Software; *Hudl* Guest Speak	Pascal Bauer, TBD
30.10.2026	Expert Lecture—Performance Analysis & Data Science in Elite Sports	TBD
06.11.2026	Student Presentations	TBD
13.11.2026	Student Presentations	TBD
20.11.2026	Student Presentations	TBD
27.11.2026	Student Presentations	TBD
04.12.2026	Student Presentations	TBD
11.12.2026	Student Presentations	TBD
18.12.2026	Student Presentations; Introduction to Hands-On Projects	TBD
08.01.2027	Hands-On Session	In-Class Project Development
15.01.2027	Hands-On Session	In-Class Project Development
22.01.2027	Hands-On Session	In-Class Project Development
29.01.2027	Hands-On Project Presentations	All
05.02.2027	Semester Summary, Gradings & Course Evaluation	All

Hands-on Projects using Data from Elite Sports

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- ***Option 1: Coding***
  - *ELO ranking using tennis data*
  - *Expected goals using football event data*
- ***Option 2: Interactive Visualisation***
  - *Data-Storytelling by creating web-based interface applications or BI-dashboard*
- ***Option 3: Video Analysis*** ***(only for HPS students)***
  - *Opponent analysis using tactical feeds and video analysis tools*

python™ R

Lovable

tableau Power BI

hudlsportscode

Guidelines

Student Presentations

- 👥 1-3 Students per group (depending on the number of students)
- ⏱️ 15 Minutes presentation + Q&A
- 🗣️ All group members must contribute into presenting
- 📤 Share presentations & documents with the lecturer and all students at least **two days before** the presentation

Hands-on Projects

- 👥 2-4 Students per group (depending on the number of students)
- ⚙️ Choose one task among:
  - *Coding **(mandatory for CS and DSAI students)***
  - *Video Analysis*
  - *Dashboard Development*
- ❓ Hands-on sessions run in a **Q&A format**
- 🏁 Present hands-on project results (10-min presentation)
- 📤 Submit slides and other project outcomes (e.g., dashboard, annotated videos)

Multiple-Choice Tests & Attendance

- 👥 **Attendance counts**: All sessions (excurion, reading group, student presentations, hands-on sessions, delayed attendance, etc.) will be aggregated as one part of the grade.
- 🌟 **Bonus points**: Attending "optional" sessions can earn you additional credit.
- 📖 **Be prepared**: Come prepared for all presentations (not just your group's!) and engage actively in the sessions.
- 📝 **Multiple-choice test**: After each presentation, a 5-min quiz will test comprehension. The two lowest scores can be dropped.

Project Submission (for CS/DSAI students taking 7 ECTS)

- The submission should be based on students' hands-on project and be in a standard academic manner (e.g., posters containing Introduction, Methods, Results, and Discussion sections).
- Code should be submitted in online repositories.

Grading Breakdown (CS/DSAI; 7-Credit Version)

Student Presentations (25%)

- Evaluated on **9 equally weighted criteria** (Preparation, Slides, Storyline, Style of presentation, Question Answering, Scientific Evidence, Literature, Timing)
- Each criterion graded **0–100 points**
- Grades may vary within a group if individual performance stands out

Multiple-Choice Tests & Attendance (20%)

- **Up to 2 absences** allowed; optional sessions (excursion session, reading group) can be used as compensations
- **2** lowest multiple-choice test results can be dropped (incl. non-attended)
- Each criterion graded **0–100 points**

Hands-on Project (25%)

- Evaluated on objective criteria for each task, with task complexity considered
- Each criterion graded **0–100 points**

Project Submission (30%)

- Evaluated on **equally weighted criteria** depending on the submission format (e.g., posters will be evaluated according to *visual Layout and design* and *scientific content and rigor*).

Final Grade Calculation

Score between 1 and 100 =

0.25 * Student Presentation

+ 0.2 * MC Tests & Attendance

+ 0.25 * Hands-on Project

+ 0.3 * Final Paper

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Translation to Grades

1,0 to 5,0

Grading Breakdown (HPS; 5-Credit Version)

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Student Presentations (40%)

- Evaluated on **9 equally weighted criteria** (Preparation, Slides, Storyline, Style of presentation, Question Answering, Scientific Evidence, Literature, Timing)
- Each criterion graded **0–100 points**
- Grades may vary within a group if individual performance stands out

Multiple-Choice Tests & Attendance (20%)

- **Up to 2 absences** allowed; optional sessions (excursion session, reading group) can be used as compensations
- **2** lowest multiple-choice test results can be dropped (incl. non-attended)
- Each criterion graded **0–100 points**

Hands-on Project (40%)

- Evaluated on objective criteria for each task, with task complexity considered
- Each criterion graded **0–100 points**

Final Grade Calculation

Score between 1 and 100 =

0.4 * Student Presentation

+ 0.2 * MC Tests & Attendance

+ 0.4 * Hands-on Project

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Translation to Grades

1,0 to 5,0

Topics

#	Topic	Reading Materials
1	**Performance Quantification Metrics in Golf**	Broadie, M. (2012); Fearing, D. et al (2011); Drappi, C., & Co TK, L. (2019)
2	**Performance Quantification Metrics in Football**	Lignell, E., et al (2020); Adams, M., et al (2023); Anzer, G., & Bauer, P. (2021)
3	**The Relative Roles of Skill and Chance in Sports**	Getty, D., et al (2018) ; Lopez, M. J., et al (2018)
4	**Objectivity and Quantification of Events and Tactical Patterns in Sport**	Low, B., et al (2021); Forcher, L., et al (2023); Forcher, L. et al (2024)
5	**Rating & Ranking Systems in Sports**	Leitner, C., et al (2010); Blog-Elo Ratings; UdS Table Tennis Course Evaluation
6	**Psychological Beliefs versus Statistical Evidence in Sports (e.g. Hot Hand, Clutch Performance, Choking under Pressure)**	Bar-Eli, M., et al (2006) ; Gilovich, T., et al (1985); Meffert, D., et al (2021)
7	**Contextualised Physical-Tactical Performance in Football**	Ju, W., et al (2023); Ju, W., et al (2022)
8	**Laterality Advantages in Sports**	Grondin, S., et al (2024); Roberts, R., et al (2010)
9	**Data-Driven Talent Identification and Prediction in Sports**	El-Feel, S., et al (2025); Jauhiainen, S., et al (2019); Barron, D. et al (2020)

(Topics subject to further changes)

Full reference lists can be found below

Datasets

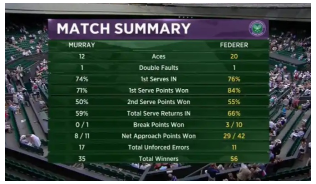
Video Footage

Event Data

Low — *Granularity* — High

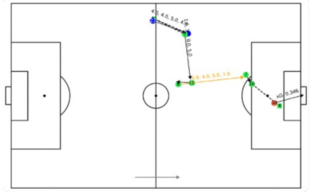
Match Statistics

- Aggregated match summaries of sports specific events
- Low dimensional and easy to interpret
- Describe overall outcomes and patterns



Play-by-Play

- Time-ordered sequence of individual events
- High temporal and contextual detail
- Enables dynamic and process-level analysis



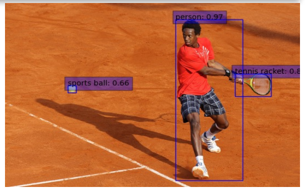
Tracking Data

2D Coordinates

- x/y coordinates of ball, players & referee
- Derived from video footage, and/or GPS/LPS systems
- >10 data points per second

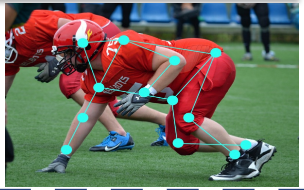
3D Coordinates

- x/y/z coordinates of ball, players & referee
- Derived mainly from video footage, and/or LPS systems



Limb Tracking

- Detailed tracking data of players' limbs and joints
- Derived from video footage + computer vision



Player Data: *Age, Height, Handedness, Career Length, Career Win Percentages etc.*

Datasets (Number of Matches Available per Sport)

		⚽	🎾	🤾	⛳	🏐	🏓	🏏	🏀
Event	**Match Summaries**	~45K[1]	~353K[2]	~14K[5]	>10K[3]	>10K[3]	>10K[3]	>10K[3]	>10K[3]
	Play-by-Play	~136M[1]	~18K[2]	>10K	-	>20K	-	~2.1K[4]	-
Tracking	**Video**	>1M[6]	>100	>100	-	128[8]	50	-	-
	2D Coordinates	326[1]	-	-	-	-	-	-	-
	3D Coordinates	55[7]	-	-	-	-	-	-	-
	Limb-Tracking	5[9]	1	-	-		-	-	-

—We are dedicated to making more data resources available for students—

1 Provided via HudlStatsbomb: https://github.com/statsbomb/open-data | 2 Provided via Jeff Sackmans Github: https://github.com/JeffSackmann | 3 Provided via https://developer.sportradar.com/getting-started/docs/get-started |4 Provided via https://cricsheet.org/ | 5 Provided via HBL: https://www.daikin-hbl.de/de/hbl/spielplan | 6 Provided via Hudl WyScout: https://www.hudl.com/en_gb/products/wyscout | 7 Provided via Bassek et al. 2025: https://www.nature.com/articles/s41597-025-04505-y | 8 Provided via Deutscher Volleyball Bund | 9 Provided via Fifa |

Topics & Materials Instructions

- Every student or group of students must select one topic which they will prepare and present at one of the „student presentation" sessions.
- Exemplary links and documents are provided with the topic as an introduction. For the presentation we expect students to do their own literature research on the topic.
- If not all topics will be covered by students, we are going to cover the sessions as teacher's presentation or in a reading group format.
- All students are expected to prepare and/or follow each session (whether it is their topic or not) so that they are able to answer MC-questions at the end of each session.
- Students are more than welcome to come up with their own topics for presentations.

GitHub Usage & Documentation Guidelines

1. GitHub may be used for version control, collaboration, and code sharing throughout the seminar.
2. All repositories must clearly reflect individual and group contributions.
3. Each repository must include a README.md describing:
   - Project goal and scope
   - Data sources and preprocessing steps
   - Code structure and usage instructions
4. Properly cite sources and licenses if any external code or templates are used.
5. Repositories must be accessible to instructors for review and evaluation

Use of Large Language Models (e.g. ChatGPT)

1. The use of Large Language Models (LLMs), such as ChatGPT, is generally permitted within the scope of this seminar. However, their use is subject to full transparency and proper documentation.
2. Any content that has been fully or partially generated with the help of LLMs must be clearly and explicitly disclosed. This includes, but is not limited to:
   - Textual content (e.g. written assignments, summaries, code, translations)
   - Images or other visual material
   - Brainstorming activities, idea generation, concept development, or structural suggestions
3. The documentation must at least specify:
   - which tool was used (e.g. ChatGPT)
   - for what purpose it was used (e.g. ideation, drafting text, image generation)
   - to what extent the generated content was adopted, modified, or further developed

Our Teaching Offers

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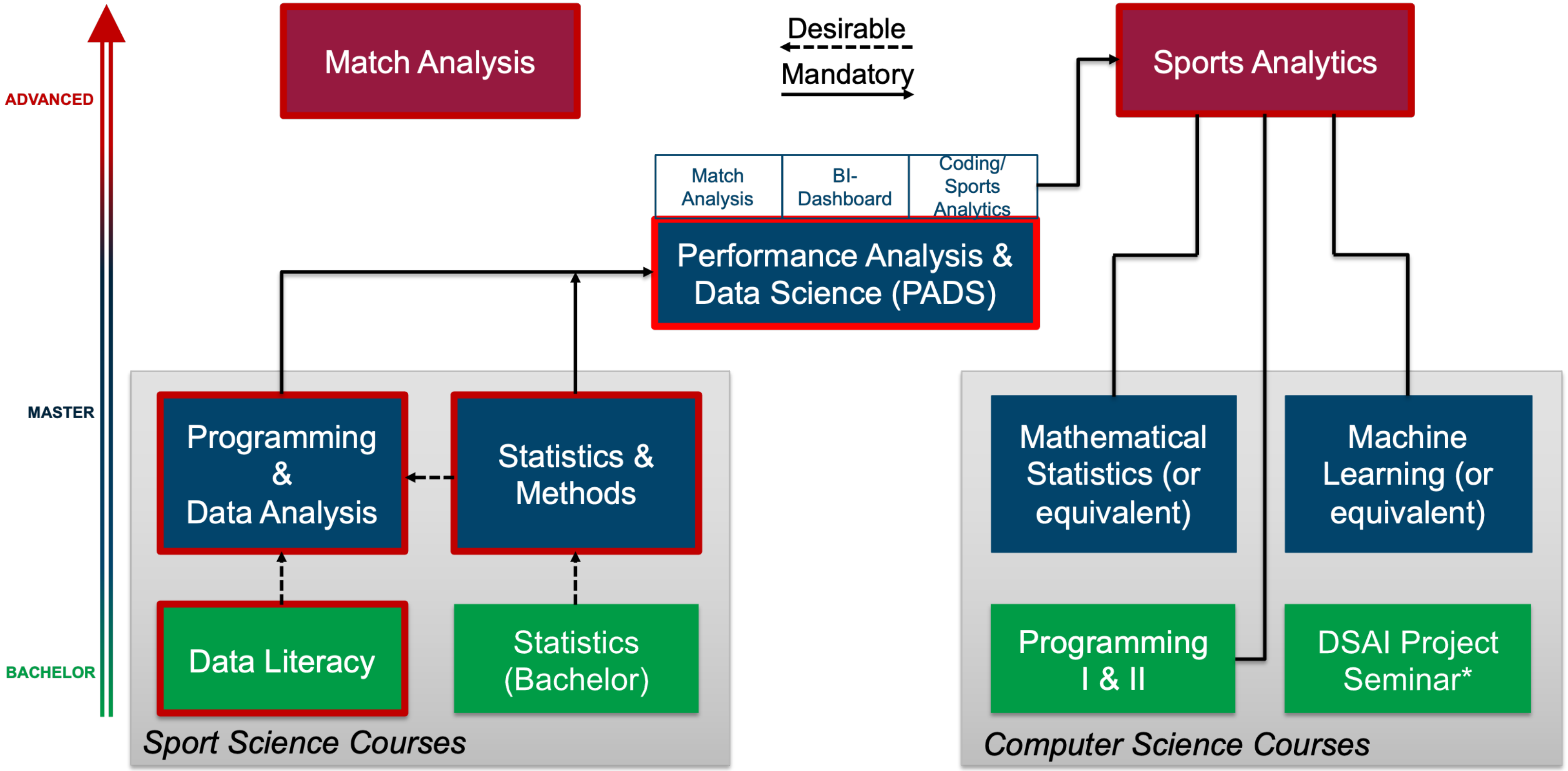

Reading Group

- Weekly online reading group where we discuss sports analytics literature
- Open access for all sports analytics enthusiasts
- English and no credits

Boxes with a red frame are teached by the chair of sports analytics

*Sports Analytics Task

References: Golf Performance Analysis: Strokes Gained and other Golf Performance Metrics (SG)

1. Pan, X., Soh, K.G., & Jaafar, W.M.W. (2026). Assessment of golf-specific skill performance: a systematic review, 3D visualization, and standardized testing framework. European Journal of Applied Physiology.
2. Broadie, M. (2012). Assessing Golfer Performance on the PGA TOUR. Interfaces.
3. Fearing, D., Acimovic, J., & Graves, S. C. (2011). How to Catch a Tiger: Understanding Putting Performance on the PGA TOUR. Journal of Quantitative Analysis in Sports.
4. Swartz, T. B. (2009). A New Handicapping System for Golf. Journal of Quantitative Analysis in Sports.

References: Finishing Ability (FV)

1. Baron, E., Sandholtz, N., Pleuler, D., & Chan, T. C. Y. (2023). Miss it like Messi: Extracting value from off-target shots in soccer. Journal of Quantitative Analysis in Sports.
2. El-Feel, S., Samir, A., Abuzahra, M., & Sharaf, N. (2025, August). TalentVision AI: A Data-Driven Framework for Tactical Player Scouting and Team-Specific Talent Discovery. In 2025 29th International Conference Information Visualisation (IV)
3. Spearman, W. (2018). Beyond expected goals. MIT Sloan Sports Analytics Conference Proceedings.

References: Expected Goals in Team Sports (XG)

1. Cefis, M., & Carpita, M. (2025). A new xG model for football analytics. Journal of the Operational Research Society.
2. Scholtes, A., & Karakuş, O. (2024). Bayes-xG: Player and position correction on expected goals (xG) using Bayesian hierarchical approach. Frontiers in Sports and Active Living.
3. Adams, M., David, A., Hesse, M., & Rückert, U. (2023). Expected goals prediction in professional handball using synchronized event and positional data. Proceedings of the 6th International Workshop on Multimedia Content Analysis in Sports.
4. Hewitt, J. H., & Karakuş, O. (2023). A machine learning approach for player and position adjusted expected goals in football (soccer). Franklin Open.
5. Karim, H., & Marwane, L. (2023). The Kos angle, an optimizing parameter for football expected goals (xG) models. International Journal of Computer Science in Sport.
6. Anzer, G., & Bauer, P. (2021). A goal scoring probability model for shots based on synchronized positional and event data in football (soccer). Frontiers in Sports and Active Living.
7. Robberechts, P., & Davis, J. (2020). How data availability affects the ability to learn good xG models. In U. Brefeld, J. Davis, J. Van Haaren, & A. Zimmermann (Eds.), Machine Learning and Data Mining for Sports Analytics. MLSA 2020. Communications in Computer and Information Science.

References: Finishing Ability (FV)

1. Baron, E., Sandholtz, N., Pleuler, D., & Chan, T. C. Y. (2023). Miss it like Messi: Extracting value from off-target shots in soccer. Journal of Quantitative Analysis in Sports.
2. González-Jarrín, P., Fernández-Fernández, J., García-López, J., & García-Tormo, J. V. (2025). Finishing patterns and goalkeeper interventions: A notational study of shot effectiveness in europe's top football leagues. Applied Sciences.
3. Spearman, W. (2018). Beyond expected goals. MIT Sloan Sports Analytics Conference Proceedings.

References: Expected Passes (XP)

1. Takamido, R., Ota, J., & Nakamoto, H. (2025). PassAI: An explainable machine learning framework for predicting soccer pass outcomes using multimodal match data. IEEE Access.
2. Rahimian, P., Kim, H., Schmid, M., & Toka, L. (2024). Pass Receiver and Outcome Prediction in Soccer Using Temporal Graph Networks. In U. Brefeld, J. Davis, J. Van Haaren, & A. Zimmermann (Eds.), Machine Learning and Data Mining for Sports Analytics.
3. Robberechts, P., Van Roy, M., & Davis, J. (2023). Un-xPass: Measuring soccer player's creativity. Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining.
4. Anzer, G., & Bauer, P. (2022). Expected passes: Determining the difficulty of a pass in football (soccer) using spatio-temporal data. Data Mining and Knowledge Discovery.
5. R, R., Harell, A., & S, P. (2022). Pass evaluation in women's Olympic ice hockey. Proceedings of the 5th International ACM Workshop on Multimedia Content Analysis in Sports.
6. Radke, D., Radke, D., Brecht, T., & Pawelczyk, A. (2021). Passing and pressure metrics in ice hockey. Artificial Intelligence for Sports Analytics (AISA) Workshop.
7. Arbués-Sangüesa, A., Martín, A., Fernández, J., Ballester, C., & Haro, G. (2020). Using player's body-orientation to model pass feasibility in soccer. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops.
8. Szczepański, Ł., & McHale, I. (2016). Beyond completion rate: Evaluating the passing ability of footballers. Journal of the Royal Statistical Society Series A: Statistics in Society.

References: The Relative Role of Skill v.s. Chance in Sports (SvL)

1. Aoki, Y. S., Assuncao, M., & Vaz de Melo, O. S. (2017). Luck is hard to beat: The difficulty of sports prediction. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
2. Lopez, M. J., Matthews, G. J., & Baumer, B. S. (2018). How often does the best team win? A unified approach to understanding randomness in North American sport. The Annals of Applied Statistics.
3. Rosker, J., & Majcen Rosker, Z. (2021). Skill level in tennis serve return is related to adaptability in visual search behavior. Frontiers in Psychology.

References: Data-Driven Talent Identification

1. Barron, D., Ball, G., Robins, M., & Sunderland, C. (2023). Identifying playing talent in professional football using artificial neural networks. Journal of Sports Sciences.
2. Lopez, M. J., Matthews, G. J., & Baumer, B. S. (2018). How often does the best team win? A unified approach to understanding randomness in North American sport. The Annals of Applied Statistics.
3. Jauhiainen, S., Äyrämö, S., Forsman, H., & Kauppi, J. P. (2019). Talent identification in soccer using a one-class support vector machine. International Journal of Computer Science in Sport.

References: The Concept of Match Phases and Tactical Patterns in Sports (MP)

1. Bauer, P., Anzer, G., & Shaw, L. (2023). Putting team formations in association football into context. Journal of Sports Analytics.
2. Stöckl, M., Seidl, T., Marley, D., & Power, P. (2021). Making offensive play predictable - Using a graph convolutional network to understand defensive performance in soccer. MIT Sloan Sports Analytics Conference.
3. Anzer, G., Bauer, P., Brefeld, U., & Fassmeyer, D. (2021). Detection of tactical patterns using semi-supervised graph neural networks. MIT Sloan Sports Analytics Conference Proceedings.
4. Bauer, P., & Anzer, G. (2021). Data-driven detection of counterpressing in professional football. Data Mining and Knowledge Discovery.
5. Fassmeyer, D., Anzer, G., Bauer, P., & Brefeld, U. (2021). Toward Automatically Labeling Situations in Soccer. Frontiers in Sports and Active Living.
6. Tian, C., De Silva, V., Caine, M., & Swanson, S. (2020). Use of machine learning to automate the identification of basketball strategies using whole team player tracking data. Journal of Applied Sciences.
7. Sarmento, H., Clemente, F., Araujo, D., Davids, K., McRobert, A., & Figueiredo, A. (2018). What performance analysts need to know about research trends in association football (2012–2016): A systematic review. Journal of Sports Medicine.
8. Van Haaren, J., Dzyuba, V., Hannosset, S., & Davis, J. (2015). Automatically discovering offensive patterns in soccer match data. International Symposium on Intelligent Data Analysis.
9. Wang, Q., Zhu, H., Hu, W., Shen, Z., & Yao, Y. (2015). Discerning tactical patterns for professional soccer teams: An enhanced topic model with applications. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
10. Wei, X., Sha, L., Lucey, P., Morgan, S., & Sridharan, S. (2013). Large-scale analysis of formations in soccer. International Conference on Digital Image Computing: Techniques and Applications.

References: Ranking & Rating System in Sports (RS)

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1. Ball, J., Huynh, M., & Varley, M. C. (2025). Comparing player rating systems as a metric for assessing individual performance in soccer. Journal of Sports Sciences.
2. Kiely, L., Mayew, R., & Mayew, W. (2025). An updated assessment of the predictive accuracy of World Tennis Number and Universal Tennis Ratings. ITF Coaching & Sport Science Review.
3. Walsh, C., & Joshi, A. (2024). Machine learning for sports betting: Should model selection be based on accuracy or calibration?. Journal for Machine Learning with Applications.
4. Gutiérrez-Santiago, A., Cidre-Fuentes, P., Orío-García, E., Silva-Pinto, A. J., Reguera-López-de-la-Osa, X., & Prieto-Lage, I. (2024). Women's singles tennis match analysis and probability of winning a point. Journal of Applied Sciences.
5. Im, S., & Lee, C.-H. (2023). World Tennis Number: The new gold standard, or a failure? ITF Coaching & Sport Science Review.
6. Williams, L. V., Liu, C., Dixon, L., & Gerrard, H. (2021). How well do Elo-based ratings predict professional tennis matches? Journal of Quantitative Analysis in Sports.
7. Berg, A. (2020). Statistical analysis of the Elo rating system in chess. CHANCE.
8. Gásquez, R., & Royuela, V. (2016). The determinants of international football success: A panel data analysis of the Elo rating. Social Science Quarterly.
9. Kovalchik, S. A. (2016). Searching for the GOAT of tennis win prediction. Journal of Quantitative Analysis in Sports.
10. Marcus, D. J. (2001). New table-tennis rating system. Journal of the Royal Statistical Society: Series D (The Statistician).
11. Carter, W. H., & Crews, S. L. (1974). An analysis of the game of tennis. The American Statistician.

References: Left/Right-Handed/Foot Bias (LRB)

1. Grondin, S., Fortin-Guichard, D., Dubeau, C.-A., & Tétreault, É. (2024). Linking the preference in a bilateral asymmetric task with handedness, footedness, and eyedness: The case of ice-hockey. PLOS One.
2. Onodera, K., & Takeda, M. (2023). Hand selection in dribbling phases: An analysis of non-dominant hand usage and dribble change in basketball. Sports.
3. Loffing, F., Sölter, F., & Hagemann, N. (2014). Left preference for sport tasks does not necessarily indicate left-handedness: Sport-specific lateral preferences, relationship with handedness and implications for laterality research in behavioural sciences. PLOS One.
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