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À Table! Improving Temporal Navigation in Soccer Ranking Tables

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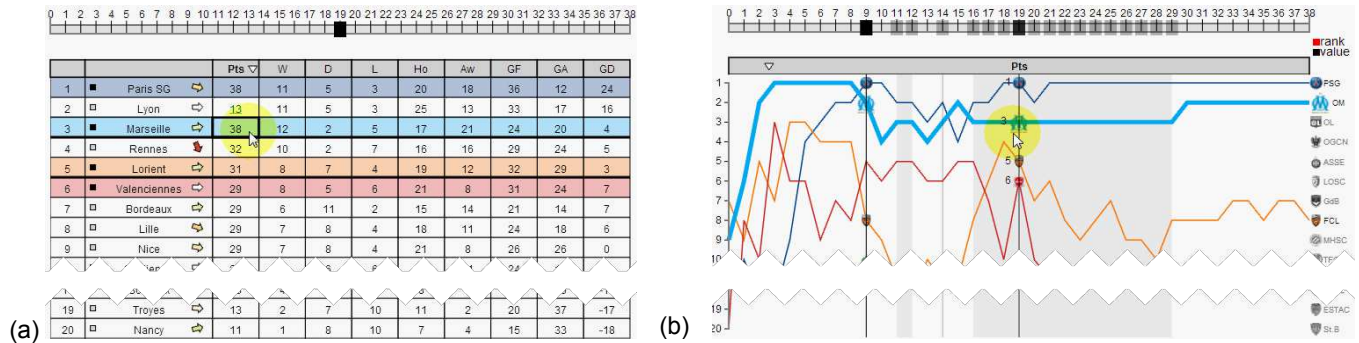


Figure 1. (a) DRAG-CELL and (b) VIZ-RANK, two novel temporal navigation techniques for ranking tables. DRAG-CELL is a direct manipulation technique to browse values over time by dragging them; VIZ-RANK uses transient visualization (line chart) to show the values of cells over time. For both techniques, the temporal slider on the top provides feedback on the current temporal navigation.

ABSTRACT

This article introduces *À Table!*, an enhanced soccer ranking table providing temporal navigation by combining two novel interaction techniques. Ranking tables order soccer teams represented as rows, according to values of columns containing attributes *e. g.*, accumulated points, or number of scored goals. Because they represent a snapshot of a championship at a time *t*, tables are regularly updated with new results. Such updates usually change the rows order, which makes the tracking of a specified team over time difficult. We observed that the tables available on the web do not support tracking such changes very well, are generally hard to read, and lack interactions. This contrasts with the extensive use of comments on temporal trends found in soccer analysts articles. To better support such analyzes, the two interactive techniques presented allow exploration of time, and are designed to preserve users' flow: DRAG-CELL is based on direct manipulation of values to browse ranks; VIZ-RANK uses a transient line chart of team ranks to visually explore a championship. An on-line evaluation with 143 participants shows that each technique efficiently supports a set of important temporal tasks not supported by

current ranking tables. This paves the way for introducing efficient advanced visual exploration techniques to millions of soccer enthusiasts who use tables everyday.

Author Keywords

Ranking Tables; Soccer; Temporal Navigation; Visualization

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION

Every day, millions of soccer enthusiasts study web sites, newspapers, or other media to learn about their favorite team's current ranking and how it compares historically. One way to present this information is to use ranking tables. Soccer ranking tables show results for a given championship, at a given day. Rows are teams, and columns are statistics. Column types include, for example: the total points per season, number of wins, draws, and lost games. Tables are updated once a round of games is over, and can become quite large. Assuming a championship with 20 teams, a table will be updated 38 times since each team plays against each other twice.

We conducted an empirical study of 51 articles (weekly and monthly summaries of soccer championships) from major soccer websites, and collected 44 pseudo-interactive soccer tables to investigate how they support temporal tasks. Our first observation was that ranking tables are not designed for comparison, despite the need for analysts and the existence

of guidelines [21, 15]. Furthermore, 77.3% of tables do not implement column sorting, and 73% of them do not provide any aid for temporal navigation although it may be useful for interactive exploration [15, 9]. Finally, we did not observe any use of visualization, however it provides compact representation for multidimensional data [15, 9] and displays trends over long time periods with line charts [13, 17].

We present *À Table!*, an enhanced ranking table combining two novel temporal navigation techniques. DRAG-CELL is a direct manipulation technique to browse values over time by dragging them into the *Value* domain; VIZ-RANK uses a line chart to show the values of cells over time, in the *Time* domain. Both techniques follow Bederson [4] principles to preserve users’ flow, to focus on tasks and prevent interruptions.

We conducted an on-line evaluation to assess how standard interactions with ranking tables (sorting and changing time with a slider), along with the two novel techniques, DRAG-CELL and VIZ-RANK, can be effective for temporal tasks. Our evaluation shows that the novel techniques efficiently support temporal tasks, which are currently not supported by ranking tables. We discuss the design implications of our improvements and give some scenarios to apply *À Table!* to other domains of application.

The contributions of this paper are as follows:

1. A Domain description and task analysis for temporal navigation techniques.
2. Two new techniques for temporal navigation in ranking tables, one in the value domain (DRAG-CELL) and one in the time domain (VIZ-RANK).
3. A crowdsourced evaluation of the two techniques along with standard navigation techniques; we then discuss which technique is well suited to which task according to the results and present the main takeaways from the experiment.

Such results provide a framework for further experiments with temporal tasks, and the design of novel navigation techniques in both the *Value* domain and the *Time* domain. Numerous application areas where ranking tables are important would benefit from these results.

BACKGROUND AND RELATED WORK

Soccer ranking tables (Figure 2) are standard ranking tables, *i. e.* tabular data vertically ordered according to values in *one* column. Ranking tables have been extensively explored using summarization, interaction and visualization techniques. As far as we know, temporal exploration in tables has never been investigated in a comprehensive way.

A rank is an ordering technique taking as input a set of items S (*e. g.*, teams) and provides a permutation of these items according to one dimension (*e. g.*, points, goals scored). A rank is a function $RANK : S \rightarrow 0, \dots, |S| - 1$, that generates up to $|S|!$ permutations, *i. e.* the number of ways the items in the set can be uniquely ordered [11]. Ranks apply to dimensions (columns) D , $|D| > 0$. Finally, a rank can be applied to *temporal* values, where $t \in T$, with T a set of discrete events (*e. g.*, games in a championship). S_{d_i, t_j} is the ranking table,

	Team	Pts	W	D	L	Ho	Aw	GF	GA	GD
1	Paris-SG	83	25	8	5	43	40	69	23	46
2	Marseille	71	21	8	9	40	31	42	36	6
3	Lyon	67	19	10	9	37	30	61	38	23
4	Nice	64	18	10	10	38	26	57	46	11
5	Saint-Etienne	63	16	15	7	37	26	60	32	28
6	Lille	62	16	14	8	34	28	59	40	19
7	Bordeaux	55	13	16	9	32	23	40	34	6
8	Lorient	53	14	11	13	36	17	57	58	-1
9	Montpellier	52	15	7	16	38	14	54	51	3
10	Toulouse	51	13	12	13	28	23	49	47	2
11	Valenciennes	48	12	12	14	33	15	49	53	-4
12	Bastia	47	13	8	17	30	17	50	66	-16
13	Rennes	46	13	7	18	23	23	48	59	-11
14	Reims	43	10	13	15	31	12	33	42	-9
15	AC Ajaccio	42	9	15	14	26	16	39	51	-12
16	Sochaux	41	10	11	17	23	18	41	57	-16
17	Evian-TG	40	10	10	18	25	15	46	53	-7
18	Nancy	38	9	11	18	20	18	38	58	-20
19	Troyes	37	8	13	17	26	11	43	61	-18
20	Brest	29	8	5	25	18	11	32	62	-30

Figure 2. Illustrative example of a “complete” table at time t , featuring the most frequent designs and embedded visualizations. Pts: number of points; W, D, L: number of Wins, Draws, Losses; Ho, Aw: number of points at Home and Away; GF, GA, GD: Goals For (scored), Against (conceded), Difference (GF-GA).

which is a *snapshot* of a championship, ranked according to a dimension d_i at a time t_j .

A soccer ranking table usually has the following properties: $|S| = 20$ teams; $|D| = 10$ dimensions; $|T| = (|S| - 1) \times 2$, *i. e.* $|T| = 38$ games; $0 \leq t \leq 38$. An important property of permutations in soccer championships is that the higher t is, the less the teams’ permutation amplitude is important because teams tend to have high points difference.

Ranking tables display tabular data and their visual design normally obey to guidelines. Tufte [21] suggests that minor visual improvements, such as vertical alignment of characters and row coloring with zebra patterns, enable comparison tasks and reduce errors. Interacting with the rank *order* help users perform some tasks (*e. g.*, finding maximum or minimum values) faster, without scanning all the rows. Many software packages, such as spreadsheets, implement ranking interactions. They also provide formulas to summarize rows for more compact representations with *Pivot tables* [23] by computing counts or totals. The same principles can be applied to columns with statistics such as averages of multiple columns or min/max values to provide other ranking mechanisms [15].

Summarization of tables is an important challenge because rankings are often longer than the screen. Visualization techniques can provide compact representation of cells. Table-Lens [15] represents tables using Focus+Context principles, collapsing rows to their minimum size or up to a pixel. This enables representing large tables on one screen as long as the number of rows is less or equal than the number of pixels. However, one row is always expanded as a focus and the

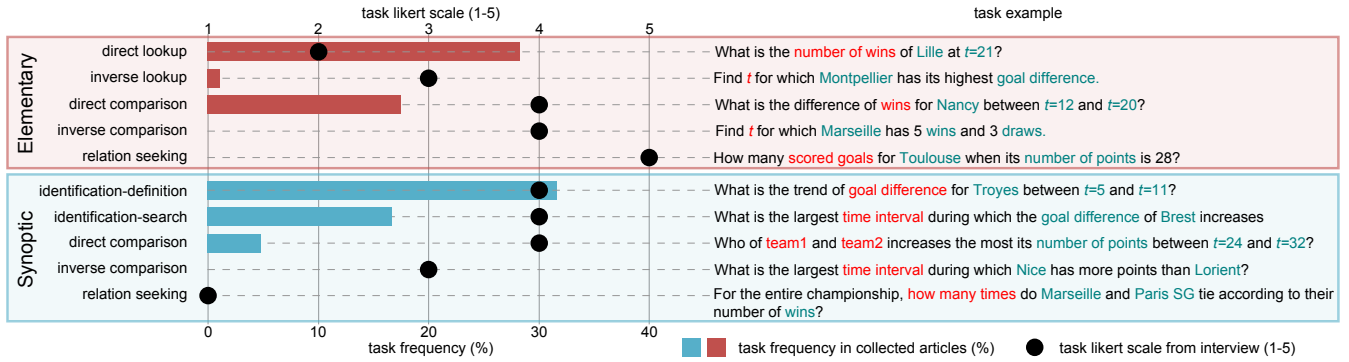


Figure 3. Extracted task categories mapped to Andrienko et al. task taxonomy for temporal data, in percent of the collected articles. Black dots indicate how a soccer expert analyst estimates each category’s relevance on a Likert scale from 1 (not relevant at all) to 5 (highly relevant). On the right are exemplary tasks for the categories. Red words are the unknown variable, blue words are the known variables.

content of the cells is visible. LineUp [9] also uses nested compact visualizations in tables, but for headers showing the distribution of values contained in the rows beneath.

Ranking also plays an important role in discovery, particularly when tables are represented as a grid layout where visual variables such as color encode values. It results in heatmap-like representations [20], and ranking becomes the primary interaction for finding patterns [16]. Such tables may become very large and require space transformation techniques, such as zooming or space folding techniques [8] to bring rows and columns back together for comparison.

Visualization techniques to display ranks are mainly inspired by line charts [13], and are also called *bump charts* because of the visual effect that permutations provide. Slope Graph [21] plots items’ *values* on two vertical axis—one for each time t_1 and t_2 —and connects similar items from one axis to another with a line. The slope of the line is a visual cue that conveys the importance of the items’ value change. However, some empty space may appear within the chart and elements may overlap. Several recent attempts produced compact charts reducing the amount of space and overlapping, while handling scalability. RankExplorer [17] shows items ranking as a flow, with glyphs wherever two items swap their ranks, or when an item has a particular increase in rank. Generally, visualization techniques are low-dimensional projections of data, that do not keep the original multidimensional flavor and interactivity of tables. They may also break users’ flow [4] because tabular layouts are too different from line charts, which require a cognitive overhead for users to connect both.

In summary, existing table improvements tackle the challenge of better sorting, summarizing, and visualizing tables. These techniques are usually not trivial for a non-expert, which may explain why we did not find any in our empirical study. Another reason might be that techniques are not specifically tailored for temporal navigation, as time is usually a tricky dimension that requires specific attention.

EMPIRICAL STUDY OF SOCCER RANKING TABLES

We conducted an empirical study to better understand current soccer ranking tables design practices. Over the 44 tables we collected, we observed that temporal navigation is rarely supported, unless the table uses non-dynamic drop-down lists.

We also investigated the use of time in soccer newspapers by collecting 51 articles. We realized that they constantly refer to temporal trends or team performances during a time period, that current table designs do not support well.

Time in Soccer Articles

We collected and analyzed 51 soccer articles, mainly from two highly influential and visited websites: L’équipe¹ (70%) weekly summaries for the entire 2012/2013 Ligue 1 Championship in France; and premierleague.com² (20%) monthly summaries of the 2012/2013 Premier League Championship in the UK. This was completed with articles from Yahoo sports, Wikipedia and other soccer websites (10%). The articles we collected outlined main events of the week or month, and illustrated them with statistics.

Out of the articles, we extracted up to 33 different tasks the journalists had to perform to write these summaries. Then, we grouped similar tasks into *generic* categories. For example, both tasks “What is the number of points of Paris SG at week 17?” and “How many goals has Marseille scored until week 5?” are subtasks of the generic category “What is the *VALUE* of *TEAM* at t ?”, where *TEAM* and t are the two known variables and *VALUE* the unknown one. This grouping resulted in 18 generic task categories.

We observed that all the tasks categories are temporal. Indeed, even the most basic task, such as “What is the *VALUE* of *TEAM*?” implies knowing when to look at the value. When t is not explicitly written, it is implicitly the latest week of the championship. We also observed that the most important column for ranking tables is the number of points of a team, determining its rank in the championship. However, the other dimensions also occur, to improve the summary details and analysis. For example, analysts often report: the number of scored goals or wins for the last n games of a team; the team’s performances at home; or a series of consecutive games with the same result (*e. g.*, 5 losses in a row).

To structure our analysis, we mapped the categories to the task taxonomy for temporal data by Andrienko et al. [3]. Figure 3 illustrates the mapping and provides examples. They classify

¹<http://www.lequipe.fr>

²<http://www.premierleague.com/>

the tasks into two categories. 1) *Elementary tasks* are *local* tasks where the object of interest is a given value or a given time. For example, such tasks are value estimation (e. g., finding extrema [1]), comparison of values at different times and time retrieval according to a given value. 2) *Synoptic tasks* are *global* tasks involving the user to take into account a set of values or a time interval. For example, such tasks are trend estimation, trend comparison, and finding time intervals with a given trend. Both categories contain *direct* and *inverse* tasks. Direct tasks consist of estimating a value or a trend according to a given time or time interval. Inverse tasks consist of estimating the time or time interval for which a dimension has a given value or trend. Finally, *relation-seeking* tasks consist of finding relations between dimensions, values and time. For example, such a task consists of comparing the value of a dimension for one team with the value of another dimension of another team, at different times.

We also conducted an interview with a soccer analyst in charge of an influential French web site³ and asked him to evaluate the fitness of each task category for soccer (Figure 3, Likert scale values). One interesting result is that the expert considers some *categories* to be important, despite not found in articles (e. g., elementary relation-seeking tasks), suggesting that those tasks are probably unconsciously in the head of our expert but that he can not perform them with his current tools.

The expert and the task analysis together legitimate the tasks that we classified in the taxonomy. The tasks our expert mentioned are, according to him, difficult to perform. In particular because they involve ranks that change over time, which are difficult to track with series of static tables. This suggests that journalists have important questions that they are not easily able to answer. Consequently, we focus on supporting tasks and analysis questions that occur in this particular domain (i.e. temporal navigation in ranking tables) in the rest of the paper.

Soccer Ranking Tables Visual and Interactive Design

We collected a series of 44 ranking tables for soccer, from UK (39%), France (35%), Spain (11%), Argentina (9%), Brazil and US (3% each). We extracted and ranked the visual features of the collected tables, such as colors and decorations.

An example of an important feature in soccer tables is the background color for the top- k ranks, such as the top-3 ranks that qualify for the Champion’s League. Or the bottom- k that indicates which team will downgrade to a minor league. Such an apparently small visual aid is actually very useful, to immediately know which team will earn additional revenues with Champion’s Leagues games, or will lose revenues by playing in a less popular league the next year.

For the top-3 rank, we found that only 50% of the tables highlight the corresponding areas, and their design is inconsistent (e. g., icons, colored rows, bold/dashed separators, colored text, and gray scale). Tables also make use of Zebra (50%) and embed visualizations: 27.3% show team logos, 29.5% add an icon encoding the latest ranking evolution, and 13.6% represent the latest results using colored circles. As a reference, Figure 2 shows a *full* table, with the most frequent features.

³<http://www.cahiersdufootball.net/>

One of the main takeaways from our findings is that interaction is rarely available. At best, the table provides the most common column sorting (for 22.7% of analyzed ranking tables). At times, the table provides widgets to interact with the temporal dimension: dropdown lists (11%), range selection (6.8%), next/previous arrows (4.5%), discrete slider (2.3%). However, it usually triggers a page reload, making the tracking of changes between the two tables difficult.

We also observed an interesting type of ranking table mapping rows on an absolute scale (linear scale of values, in this case points) rather than the relative scale (linear scale of ranks). It is referred as *Absolute scale rank*. Similarly as for Slope Graph [21], it gives a better idea of the team’s distribution at a given time. However, it requires more space as the count of rows for such a table is not the number of teams, but the difference of points between the first and the last team.

Time Navigation

Only 27% (12/44) of the tables implement temporal navigation while both soccer ranking tables and analyst tasks heavily rely on time. When available, changing t is usually cumbersome, with standard widgets—certainly because implemented in every GUI—such as:

- Drop-down lists to directly jump to a specific time. They cannot be used to dynamically browse a time interval but are very efficient to select a particular time.
- Arrow widgets to jump to previous or next tables, with some shortcuts to the beginning or the end of the championship. They are efficient to navigate sequentially, step by step.
- Range slider for 6.8% (3/44), to select the data in $[t_i, t_j]$ and compute the cell values between these two times.
- slider for 2.3% (one table) to support temporal navigation, similarly to a seeking bar to scrub videos.

The results from our study highlight the lack of temporal navigation mechanisms, and only one table featured a slider which would be recommended as an efficient way to explore such a quantitative data space [19]. We are not able to give any explanation. From a technical perspective, standard widgets are implemented in <HTML> and the data to compute ranking tables are relatively small and freely available. From a user perspective, we showed a dynamic slider to our soccer expert and he found it of great value, wondering himself why he does not provide one on his website.

IMPROVING TEMPORAL NAVIGATION

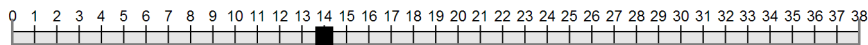
À *Table!* is an advanced ranking table that includes current ranking table practices (Figure 4), with two novel techniques for temporal navigation: DRAG-CELL is based on direct manipulation of values to browse ranks; VIZ-RANK uses a transient visualization of team ranks (line chart) to explore a championship. Those techniques aim at improving the support of temporal tasks we introduced in Figure 3.

Features from Current Ranking Tables

À *Table!* is a ranking table, along with the following features:

- *Temporal Slider* to give both an overview of the championship, and to provide a continuous temporal navigation.

Explore the ranking table of the 2012/2013 French Ligue 1



		Pts ▾	W	D	L	Ho	Aw	GF	GA	GD
1	□ Lyon	28	8	4	2	18	10	27	15	12
2	■ Paris SG	26	7	5	2	14	12	23	10	13
3	□ Marseille	26	8	2	4	14	12	18	15	3
4	□ St Etienne	25	7	4	3	16	9	24	10	14
5	□ Bordeaux	24	6	6	2	12	12	18	11	7
6	□ Valenciennes	22	6	4	4	15	7	27	16	11
7	□ Toulouse	22	6	4	4	12	10	23	16	7
8	■ Rennes	22	7	1	6	12	10	18	17	1
9	□ Lille	20	5	5	4	11	9	16	15	1
10	□ Nice	19	4	7	3	12	7	19	19	0
11	■ Lorient	18	4	6	4	12	6	22	27	-5
12	□ Montpellier	17	4	5	5	9	8	19	18	1
13	□ Ajaccio	17	4	5	5	8	9	15	19	-4
14	□ Brest	17	5	2	7	16	1	14	18	-4
15	□ Bastia	17	5	2	7	12	5	21	33	-12
16	□ Reims	16	4	4	6	14	2	13	14	-1
17	□ Evian	15	4	3	7	6	9	16	22	-6
18	■ Sochaux	14	4	2	8	7	7	13	20	-7
19	□ Troyes	8	1	5	8	7	1	14	29	-15
20	□ Nancy	7	1	4	9	5	2	9	25	-16

Score: 0

Level: 1/12

What is the outcome (win, draw, or loss?) of Bastia at day 30?

Win ☐ Draw ☐ Lost ☐

OK

High Scores

1	Capitaine	9609
2	Adrien9	9601
3	Fugazi	9186
4	Nannig	9172
5	Theo_17	8988
6	Axi	8894
7	M. Gorsky	8316
8	M. Gorsky	8263
9	Chris	8088
10	kad	8060

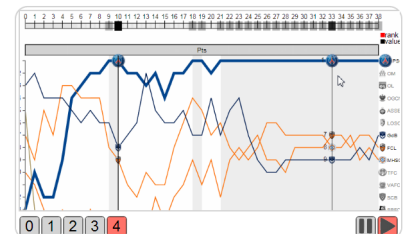


Figure 4. *À Table!* integration into a web page for on-line evaluation. The interactive table along with the temporal slider is on the left; the quiz, the high scores and navigable animated GIFS as explanations on the right.

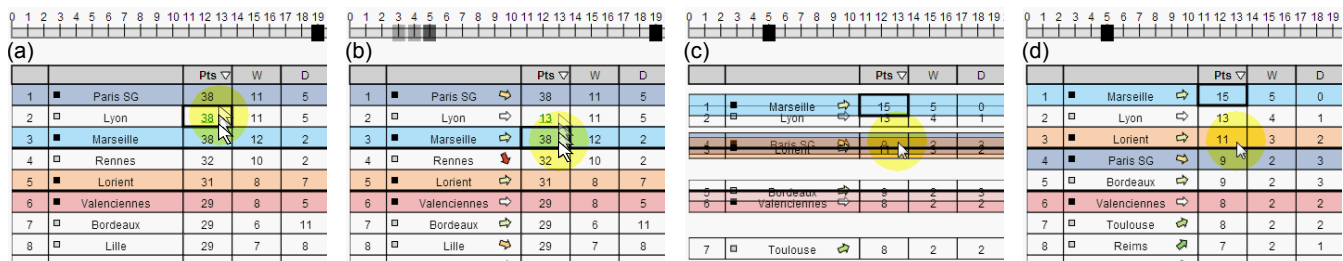


Figure 5. DRAG-CELL: (a) dragging up and down the value of a cell (in this case, Points of Team Lyon) makes this value change (b) for the set of values it can have, and colored arrows indicate how teams would behave if the drag was released (green to red arrows). (c-d) Releasing the drag animates the rows to their new position.

The slider is also synchronized with the two new interaction techniques we describe below to convey visual feedback.

- *Multiple teams selection* by clicking on team names to select and highlight their row, to facilitate their tracking over time.
- *Column sorting* by clicking on the table's headers to apply the rank function over a specific dimension.

Design Philosophy for the Novel Techniques

We designed DRAG-CELL and VIZ-RANK with the challenge of preserving users' flow. We followed Bederson [4] principles by supporting both novice and experts with the same display. While tabular display remains the default view, novel techniques are activated with specific mouse interactions and new representations are animated to prevent users' interruptions. User is always in control with incremental actions and a visual feedback to constantly show what he is doing.

Because the design space for novel techniques is important, we decided to focus on two techniques which support specific temporal tasks that ranking tables or standard widgets do not currently support: DRAG-CELL lets the user interact in the *value domain* and VIZ-RANK in the *time domain*.

Novel Technique 1: Direct Manipulation of Values

From the task analysis, we observed that the expert estimated as important several inverse tasks which were not frequent in journalist articles. Inverse tasks are challenging to perform using standard tables and it may explain why journalists avoid these tasks. We designed DRAG-CELL to make easier to perform these difficult tasks by interacting with cell values directly (*e.g.*, the number of points of a team): the user manipulates the *value domain* instead of the *time domain*, unlike standard navigation techniques such as a temporal slider. Typically, DRAG-CELL allows users to quickly find if

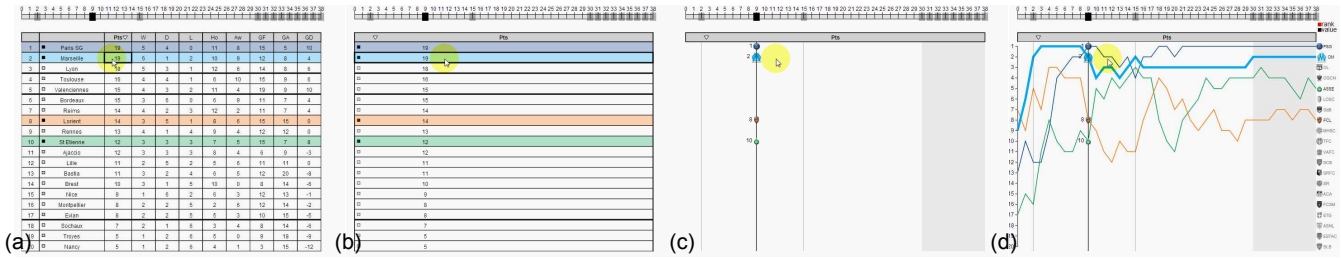


Figure 6. Table to VIZ-RANK: (a) clicking on a cell of a team for a dimension makes (b) the dimension’s column grow horizontally, stretching the other columns until they disappear; then (c-d) the cells fade out and the time series of the cell’s value for the team fades in. Line charts with a thinner stroke shows previously selected teams’ line charts.

and when a value was reached. For example, a frequent task consists of finding the time when a team reaches 42 points; this specific value being the theoretical minimum number of points a team needs to be safe from the downgrade area.

DRAG-CELL follows the principle of direct manipulation [18], with teams as objects of interest and is inspired by Tangle [22]. The visual instance of teams are rows, and each cell can be dragged to explore the values of the cell itself over t (Figure 5). Releasing the drag changes the value of t for the table to the local t_c of the cell. The user’s flow is as follows:

1. **Start:** DRAG-CELL is activated by a mouse *drag* on a cell.
2. Then by dragging the mouse up and down, the cell value changes for all possible values for this cell.
3. Arrows indicate the preview of each team’s behavior over time if the drag was released: the arrows range from pointing down and red (*e. g.*, the team is going down a lot) to heading up and green (*e. g.*, the team is going up a lot).
4. Additionally, the temporal slider displays a visual feedback as a preview of the current t_c .
5. **End:** Once the drag is released, t_c is applied to the table. Rows permute with animation to their new rank position.

Novel Technique 2: Line Charts as Transient Objects

VIZ-RANK displays a temporary or *transient* line chart when a user clicks on a cell (Figure 7). This line chart displays the teams’ ranks over the whole championship. The user can click on one point on the chart and t is set according to the corresponding value. The user’s flow is as follows:

1. **Start:** VIZ-RANK is activated by a mouse *click* on a cell.
2. Then, an animated staged transition [10] transforms the table into a time-line format by successive widening of columns and rows (Figure 6).
3. A line chart is displayed with the X-axis encoding the whole championship time range and the Y-axis the dimension of the cell the user clicked on. Each team line is encoded with Semantically-Resonant Colors [12] that matches teams’ logo (which is also displayed at the end of the lines).
4. The line chart displays by default the ranks, but the Y-axis can also encode the absolute values (Figure 7).
5. A visual feedback displays a vertical bar at the current mouse position to enable comparison. The team associated to the cell the user clicked on is highlighted.
6. **End:** When clicking on the chart, it is animated back to its table form with t corresponding to the click x coordinate.

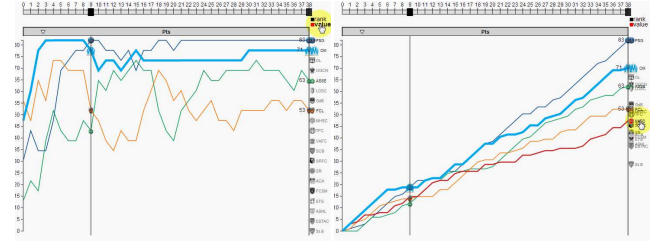


Figure 7. The two available line chart types: Rank (left) or Value (right). A click on a team’s name or logo on the right selects the team.

The staged transitions are similar to the ones from the table to the line chart, but in reverse order.

CROWDSOURCED EVALUATION

We conducted an evaluation to assess how standard interactions, along with DRAG-CELL and VIZ-RANK, can be effective for temporal tasks. We also expect to identify which task categories discriminate the techniques.

Methodology

We released *À Table!* on the web during a 3-week period, for a crowdsourced evaluation. *Crowdsourcing* is the use of an unknown public to perform simple tasks [14]. Participants (workers) are usually recruited through online markets (*e. g.*, Amazon’s Mechanical Turk) and paid to obtain results of quality. We crowdsourced the evaluation because the target user is specific (soccer enthusiast with interest in statistics) and to keep unaltered their environment (they usually browse specialized websites) without paying them. We also picked up this evaluation method because existing tables do not support dynamic temporal navigation and have very inconsistent designs, thus a traditional lab experiment with a baseline comparison would not be appropriate.

We evaluated participants’ performance using a quiz (Figure 4, top right). We designed the quiz’s questions based on the extracted tasks for soccer analysis (similar as the examples in Table 3). We also displayed the quiz high scores as an incentive to engage visitors.

Implementation

À Table! is implemented using JavaScript and D3 [5] to run in any modern web browser. The web page is available in English and French at <https://github.com/charlesperin/atable>. We implemented the table and the temporal slider on the left; the quiz and the high scores on the right (Figure 4).

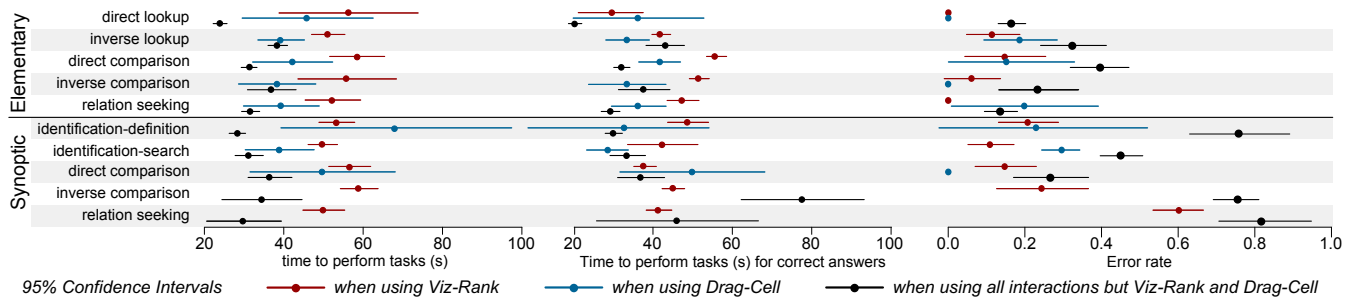


Figure 8. Time and Error for each task category, by performed interactions.

We also added a tutorial as instructions for the novel techniques on the bottom right, using a slide-show of animated GIFs. A help button at the bottom opened a help page on how to use the table. The experimental setting is available at <http://charles.perin.free.fr/atable>. We collected feedback from participants with an on-line questionnaire, reached either by clicking on a feedback button or once the quiz is completed. We used the data from the French Ligue 1 2012/2013 championship.

Hypotheses

Our hypotheses for the experiment are as follows:

- H1:** side tutorials will help users to activate and learn the novel techniques, even without visual cues or affordances on the table.
- H2:** the temporal slider will be faster for elementary direct lookup/comparison because these tasks only require changing t and browsing the table.
- H3:** DRAG-CELL will be the fastest for elementary inverse lookup/comparison tasks, tasks it was designed for.
- H4:** VIZ-RANK will be errorless for synoptic tasks because it expresses best the temporal evolution of values over the whole time span.
- H5:** VIZ-RANK will be slower for all tasks because the mental representation of the teams for users changes.

Tasks

Participants performed tasks issued from each category (Figure 3) using our previously set of 33 tasks. We equally distributed elementary and synoptic tasks. Task variables were randomly generated with some constraints to avoid trivial tasks where the participant's knowledge of the data would be enough to answer. Participants had to answer 36 questions correctly to complete the quiz.

Participants

We recruited participants by advertising the web page URL using social networks, mailing lists and soccer forums, to select appropriate participants interested in soccer and statistics.

Incentive Impact: after two weeks, among the 141 visitors who resulted in 242 tasks performed, only **one** fully completed the quiz and answered the questionnaire. We observed the following recurring pattern: most visitors interacted with the table, answered a few questions and then dropped out without finishing the quiz. To encourage visitors to answer more questions and eventually complete the quiz, as an incentive we

advertised free cinema tickets to participants with the highest scores. This immediately resulted in a stronger engagement from the participants.

Demography: we extracted the following informations from Google Analytics: most of the visitors were from France (60.5%), then United States (17.4%), United Kingdom (4.9%) and Canada (3%). 53.1% used French and 46.9% English.

Participation Logs

We logged all participants' interactions, such as: column sorting, team highlighting, slider navigation, DRAG-CELL and VIZ-RANK interactions. We recorded the following values for each quiz answer: quiz session, question number, id, and category; time to perform the task; participant's answer; correct answer; associated interactions ids.

Results

Over a 3-week period, we registered 1292 visits and 648 visitors performed at least one task. We discarded the data for participants who performed less than 10 tasks and the 239 answers longer than 120 seconds. 143 performed more than 10 tasks (*G1*), 62 participants completed the quiz (*G2*) and 34 filled the questionnaire. Only participants who completed the quiz filled the questionnaire. This results in 6693 tasks performed and 185 636 interaction logs.

Quantitative results: participants used VIZ-RANK for 31% of their answers, DRAG-CELL for 9%, and exclusively the other features for 60%. We performed the quantitative analysis using *G1* results—the larger dataset—because we did not find any significant difference between *G1* and *G2*. Figure 8 shows the time and error for all task categories according to performed interactions. We grouped the answers from participants using VIZ-RANK and other interactions into *VR*, DRAG-CELL and other interactions into *DC*, and other interactions (exclusively) into *O*. When both DRAG-CELL and VIZ-RANK were triggered, we counted the last interaction as the one that led to the answer. We performed Anovas when the data had a normal distribution (we applied a log transform to the measures of time) and when the analysis of variance allowed it (Bartlett's K-squared). We used a Welch two-sample t-test (unequal sample size and variance) for pairwise means comparison. We report significant results only in Table 1.

Interactions: Figure 9 shows which interactions were performed, for correct and incorrect answers: all the interactions have a higher percentage of use for correct answers than for

Factor	Task category	F	p	Pairwise mean comparisons	Mean		
					DC	VR	O
<i>Error</i>	elementary inverse lookup	$F_{3,401} = 3$	*	$DC < O \& VR \ll O$	0.19	0.11	0.34
	synoptic identification-definition	$F_{3,406} = 3$	*	$DC < O \& VR \ll O$	0.22	0.21	0.75
	synoptic identification-search	$F_{3,423} = 5$	**	$VR \ll O$	0.28	0.11	0.45
	synoptic inverse comparison	$F_{2,143} = 27$	***	$VR \ll O$	/	0.25	0.77
	synoptic relation seeking	$F_{2,186} = 6$	**	$VR \ll O$	/	0.61	0.82
<i>Time</i> (correct answers)	elementary direct lookup	$F_{2,337} = 9$	***	$O \ll DC \& O \ll VR$	38s	33s	19s
	elementary inverse lookup	$F_{3,241} = 5$	***	$DC \ll VR$	36s	43s	45s
	elementary direct comparison	$F_{3,206} = 21$	***	$O \ll VR$	42s	58s	33s
	elementary inverse comparison	$F_{3,74} = 6$	***	$DC \ll VR \& O < VR$	36s	51s	39s
	elementary relation seeking	$F_{3,261} = 12$	***	$DC \ll VR \& O \ll VR$	35s	48s	30s
	synoptic identification-definition	$F_{3,226} = 22$	***	$O \ll VR$	32s	49s	31s

* for $p \leq 0.05$, ** for $p \leq 0.01$, *** for $p \leq 0.001$; Welch two sample t-test: $x < y$, $x \ll y$, $x \lll y$.

Table 1. Significant results for answers based on DRAG-CELL (DC), VIZ-RANK (VR), and exclusively other interactions (O). We analyzed the Error for all tasks and the Time for correct answers only.

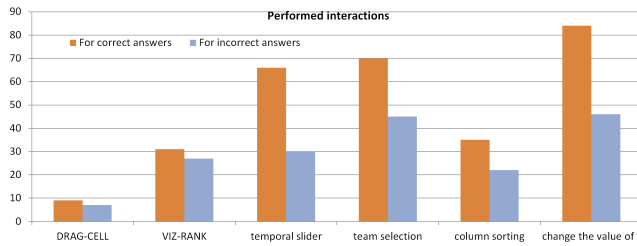


Figure 9. Percent of answers for which interactions were performed at least one time, for correct and incorrect answers.

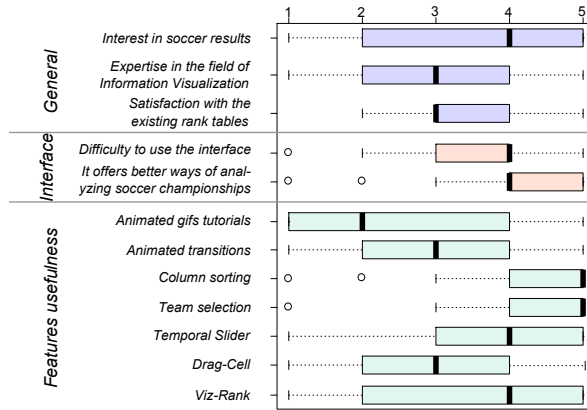


Figure 10. Answers to the questionnaire, on Likert scales [1-5].

incorrect ones. The most frequent interaction is changing the value of t (for more than 80% of correct answers) and was triggered most using the temporal slider, then VIZ-RANK and DRAG-CELL. Participants used the team selection for 70% of the tasks, and column sorting for a third.

Qualitative Results: Figure 10 shows the participant’s scores on Likert scales for their background, questions on the interface and more specific questions about *À Table!* features. The main observation is that participants’ satisfaction with existing ranking tables is low: 91% (31/34) of the participants would like to have access to such an interactive table on their favorite soccer website. Indeed, they estimate it offers better ways to analyze soccer championships (74% of the participants discov-

ered unknown information during the quiz). Interestingly, they scored the team selection, the column sorting and the temporal slider as the most useful features. However, none complained that the novel techniques were distracting, or that they were disturbing obstacles to perform the tasks.

DISCUSSION

Observations from Experiment and Main Findings

Soccer enthusiasts with heterogeneous backgrounds in Information Visualization discovered and performed *À Table!* interactions. Our investigation confirms **H1**, although users rated the interface as difficult to use. We also had to provide an incentive in order to engage participants and make them complete all the tasks.

Some participants commented that it was difficult to discover the interactions. For example, one participant wrote: “*I think it has a low discoverability for the graph and the drag in the cell*”. DRAG-CELL and VIZ-RANK are relatively advanced techniques, performed directly on the table, to let users focus on their task. For such techniques, discoverability is a well known problem (as noted by Bederson [4]). We provided a side tutorial for beginners to learn by example. However, the results showed that almost all participants discovered both techniques by exploring the table, without using this side tutorial and they often accidentally triggered the interactions the first time. In fact, both DRAG-CELL and VIZ-RANK appear to be quite discoverable without specific affordance.

Answers to the questionnaire confirm the interest from soccer enthusiasts for *À Table!*: 74% of them discovered new information and 31/34 participants gave a score higher than 3 on the 1-5 Likert scale to rate how *À Table!* offers better ways of analyzing soccer championships. For example, one participant wrote: “*wish I had it for my own championship (UK)*”.

O is faster than VR for both elementary direct lookup and comparison. This is explained because choosing the appropriate value for t is enough to perform the task well and using VIZ-RANK makes the user waste time. O is also faster than DC for elementary direct lookup, so we partially confirm **H2**.

For both elementary inverse lookup and comparison, *DC* has the lowest mean time and is significantly faster than *VR* and we partially confirm **H3**. We also note that for inverse lookup tasks, we did not find any significant difference between *DC* and *O* because the standard deviation for *O* was too high, although it was the slowest technique overall. *DRAG-CELL* was rarely used, but when it was, participants performed tasks faster and with fewer errors. These results confirm that *DRAG-CELL* is efficient to perform the tasks it was designed for.

For four synoptic tasks (identification definition, identification search, inverse comparison, and relation seeking) *VR* has significantly less error than *O*, participants making respectively 3.6, 4.1, 3.1 and 1.3 times less error using *VIZ-RANK*. We did not find any significant difference between *DC* and *VR* for these tasks but the mean error is the smallest for *VR* and we partially confirm **H4**. We also note that *DC* has less error than *O* for the identification definition task.

VR is the slowest for five out of the six tasks for which we were able to analyze time, with *VR* being almost twice as long as *O* for several tasks. For half the tasks with significant difference, *VR* is slower than both *DC* and *O* and we partially confirm **H5**. We explain this result because participants may not be familiar with line charts. However, it is not clear if this is a general issue, if this is in the context of rank visualization or because of the short apparition of the chart.

Participants used *VIZ-RANK* for complex synoptic and relation-seeking tasks that are extremely painful to perform without a dedicated technique. The technique involves fewer errors but requires more time. However, because journalists cannot afford to publish incorrect data, the technique must be accurate, even at the cost of a slight increase in completion time; comparing time between techniques makes sense when the techniques have similar error rates, which is not the case.

The main takeaways from our experiment are as follows:

- *Basic interactions remain essential, fast to operate and easy to learn for basic tasks.* However, some tasks are almost impossible to perform using only these features (up to 82% of error) and advanced interaction techniques are required.
- *Interactive techniques are crucial to explore temporal ranking tables.* The more interactions are used, the more the task is performed correctly (Figure 10).
- *DRAG-CELL is fast and error-less for the tasks it was designed for (inverse tasks)* but almost never used for other task categories.
- *VIZ-RANK is accurate and well-suited to synoptic tasks and all tasks can be performed using it.* However, it is slow to operate and requires user's basic knowledge in Information Visualization.

Finally, both *DRAG-CELL* (for elementary inverse lookup and comparison) and *VIZ-RANK* (for four out of the five synoptic tasks categories) makes it easier to perform the tasks they were designed for. Moreover, several of these tasks were almost absent from the task analysis from soccer articles but were estimated as highly relevant by the expert. We may expect that by providing such interaction techniques as *DRAG-CELL* and *VIZ-RANK*, the analysts will be able to perform tasks they

can not perform today and therefore enhance the quality of the insights and statistics they can retrieve from the data.

Applicability Beyond Soccer and Limits

À Table! is seamlessly applicable to other sport ranking tables showing team statistics. We now describe *À Table!* applicability to two types of ranking tables from different domains and discuss possible issues and limits.

Academic Rankings

Since 2003, the Shanghai University [6] publishes every year an updated Academic Ranking of World Universities. It ranks the top $|S| = 500$ institutions, with $|D| = 6$ dimensions. The main rank is computed on the number of Nobel Price or Fields Medal winners from the institution, among other criteria. Top institutions like Harvard and MIT are respectively ranked first and second, and tracking them over time can be done visually. *À Table!* would be efficient to browse the top- k , $k = 20$ ranks for which permutations are important but mostly remain on the same screen. However, some issues occur for ranks lower than 100 which are not all visible without scrolling and contain ties. Furthermore, it only ranks the top-500 universities every year, meaning that new institutions may appear or disappear over time, making their tracking difficult.

Sorting Algorithms Execution

Sorting algorithms, such as quicksort or bubble sort, perform many permutations until they end in a final result. The number of permutations varies according to the size of the dataset $|S|$. The type of permutations varies according to the algorithm itself. Existing works already explored the visualization of execution steps⁴ which enable a non-expert to grasp the underlying sorting strategy. *À Table!* would be useful to inspect executions and to reach a specific execution step or time. Such an investigation of algorithms—or any ordered dynamic process—can be used in a variety of contexts, ranging from educational purpose to algorithms optimization.

Limits

Some real-life rankings may not be immediately compatible with current *À Table!* design. It is already challenging to visualize and interact with rankings with partial ranks, missing data during time intervals, new dimensions, etc. In contrast, tables do justice to such rankings by creating empty rows or additional columns to represent missing data. It may not be optimal but it has the merit of being a consistent representation.

Design Implications

Adding novel interactive techniques to legacy techniques, such as ranking tables, implies many design considerations. We only scratched the surface of making them fully effective, and we share some lessons we learned on their discover-ability and learn-ability. Discover-ability is mainly connected to the affordance of the first interaction to **start** the technique. We did not use any for simplicity, and considered natural to change values by dragging them up and down. Some codes for affordance are already available, such as Bret Victor's [22] use of dashed lines to show draggable values. Learn-ability can

⁴<http://www.youtube.com/watch?v=m1PS8IR6Td0>

be supported in many ways. The tutorial we provided during our experiment was probably not sufficiently contextualized, explaining why most of the participants discarded it. It seems that it was natural for users to click and drag cells as they are their primary interest. They may have acquired this knowledge elsewhere and applied it to *À Table!* by associativity [2]. Line charts provide visual guides, but require space and time to appear. Exploring hybrid features, such as dragging values with a visual overlay showing upcoming and past values, might be the best of the two worlds but needs more investigation. Still, regular dragging can be left as an expert-feature [4].

CONCLUSION AND FUTURE WORK

This paper presented *À Table!*, an enhanced ranking table with improved temporal navigation, by combining two novel interaction techniques. Initially, our goal was to better support ranking tables interactivity and representation of time, as the temporal dimension is crucial to understand soccer championships. We designed novel interactions following Bederson [4] principles to preserve user's flow, to focus on tasks and prevent interruption. Our evaluation shows that the techniques efficiently support temporal tasks, currently not supported by ranking tables, while not breaking user flow. This paves the way for efficiently introducing advanced visual exploration techniques to millions of soccer enthusiasts who use tables everyday, as well as other application domains which use ranking tables.

We also thought to design novel navigation techniques to include in *À Table!*. One of them is using a table cube metaphor, with a transient 3D animation similar as Rolling the Dice [7], to change a time t or a dimension d step-by-step. This type of transition provides a consistent temporal navigation paradigm—adequate with tables which are also squared—and perfectly fits in table boundaries.

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