

# BetterRelations: Detailed Evaluation of a Game to Rate Linked Data Triples

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**Abstract.** While associations between concepts in our memory have different strengths, the explicit strengths Linked Data edge weights are missing. As a result Linked Data is of limited use for Artificial Intelligence with respect to the simulation of human thinking. In order to build a collection of such edge weights, we created a web-game prototype that ranks triples by importance. In this paper we explain the game’s concept, summarize Linked Data related implementation aspects, and include a detailed evaluation of the game.

## 1 Introduction

Since its introduction in 2001 the Semantic Web [1] has gained much attention. In recent years, especially the Linking Open Data (LOD) project contributed many large, interlinked and publicly accessible RDF datasets, generating one of the world’s largest, decentralized knowledge bases. The accumulated amount of Linked Data has many applications and can already be used to answer structured questions (e.g., the DBpedia [2] dataset can easily be used to compile a list of musicians who were born in Berlin).

Nevertheless, it currently is impossible to rank result sets—not even those of simplistic (descriptive) queries—by importance as considered by an average human. For example, asked to describe (“What/Who is ...?”) *Facebook*, nearly all humans will explain that it *is an online social network*, but only few will tell us that *Chris Hughes is one of its co-founders*.<sup>4</sup> In the remainder of this paper, we will hence call the fact “Facebook has subject online social networking” to be more *important* than “Facebook has key person Chris Hughes”.

In contrast to this, Linked Data triples, which are (subject, predicate, object)-statements, also called facts, are facts in a logical sense. Like logical axioms, they all are of the same “importance”, none being more valuable than another. This lack of explicit importance information leads to problems, for example when a user requests a concise description<sup>5</sup> for a resource.

<sup>4</sup> In this paper we focus on an “average human’s” view, leaving the application of user and context models to future work.

<sup>5</sup> Description as in SPARQL DESCRIBE queries.

A collection of such importance information would allow us to ask machines not only to give us all known facts related to a resource (e.g., all 695 triples related to Barack Obama in the DBpedia) in an arbitrary order, but also to rank this information by importance, allowing us to constrain the number of results to the most important ones (e.g., the top 10). With regard to Artificial Intelligence this would provide a basis for human-like reasoning on Linked Data and enable us to drastically reduce the search space to only those concepts strongly associated with the current context by an “average human”. Another immediate benefit from annotating Linked Data triples with association strengths is the possibility of feedback for automated extraction processes, e.g., the one underlying DBpedia. One could investigate, which extraction rules yield high and which ones yield low strengths, facilitating an improvement process.

Besides these immediate benefits, such a collection of association strengths would also allow us to investigate whether currently used heuristics (e.g., based on semantic similarities, such as estimated by word co-occurrences on websites or based on network analysis approaches, such as PageRank and TripleRank, trying to model how much activation flows from one concept to another) truly model how we associate thoughts. If this is the case, the heuristics could be used to bootstrap the acquisition of associations strengths, else such a dataset would be a valuable prerequisite to develop heuristics to estimate triple importances.

Despite all the benefits a collection of Linked Data triples rated by human association strengths would have, it suffers from the typical knowledge acquisition bottleneck. Collecting such strength values is prone to subjectivity, it is extremely monotonous and tedious, and it is difficult for humans to reliably and objectively assess the absolute strength value of a triple. Furthermore, the immense amount of Linked Data would cause great expenses if people were to be paid for rating even a small part thereof.

In order to overcome the aforementioned problems, we sketched the idea for a web-game in [3] and briefly described our findings from developing a prototype called *BetterRelations* in [4] following the “Games With A Purpose” approach by von Ahn and Dabbish [5].

In the rest of this paper give an overview of related work (Section 2), and provide a detailed description of the game’s concept as well as data acquisition and necessary preprocessing steps to present Linked Data triples to players in a comprehensible format (Section 3). Furthermore, we report on a detailed evaluation, consisting of statistics, the results of a user questionnaire and a comparison of the game results with manually generated ranked lists by a test group (Section 4), as well as a discussion of our findings, identifying possible improvements and future work (Section 5).

## 2 Related Work

In terms of game design, *BetterRelations* is related to *Matchin* [6]. *Matchin* is a two player web-game, which confronts pairs of players with two pictures (taken from the WWW), asking them which one they prefer. If the preferences of both

players match, the players are rewarded with points and an increasingly higher bonus. In case of a mismatch, they are not rewarded with points and the bonus is reset to 0. In this process, decisions which both players agree on are considered more valuable than mismatches. In the background Matchin records the pairwise user preferences and uses them to compute a global rating of the played images. In contrast, BetterRelations presents two textual facts corresponding to Linked Data triples about one topic to its players. Whereas Matchin creates a globally ranked list of images, BetterRelations computes a ranking for each topic and its related facts. Hence, the rating algorithm, which transforms the pairwise user preferences into the global ratings hence has to deal with significantly smaller lists. As detailed in Section 3.1, BetterRelations includes several additional features in order to make Linked Data issues such as noise or unknown facts tractable.

*OntoGame* [7] was the first and most prominent game with a purpose focusing on Linked Data. Nevertheless, it collects another type of information than BetterRelations: Players are asked to decide if a Wikipedia topic is a class or an instance, aiming at creating a taxonomy of Wikipedia.

*WhoKnows?* [8], a *single player* game, judges whether an existing Linked Data triple is known by testing players with (amongst others) a multiple choice test or a hangman game. In contrast to our approach, WhoKnows only uses a limited fraction of the DBpedia dataset and excludes triples not matched by a predefined domain ontology in a preprocessing step. This greatly reduces noise issues, but eliminates the possibility to collect user feedback about triple qualities and problems in the extraction process. Also, WhoKnows intends to rank triples by degree of familiarity. However, the used measurement only relies on the ratio of correctly recognized facts divided by number of times a fact was tested. The quality of this ratio is doubtful as it does not distinguish whether a fact has been tested few or many times.

Other collaborative approaches to create large knowledge bases usable by machines exist, including the Open Mind Common Sense Project (OMCS) [9] or Freebase<sup>6</sup>. Freebase shows some input methods that resemble games, such as: *Typewriter*<sup>7</sup> or *Genderizer*<sup>8</sup>. Answers taken from users in these interfaces are directly converted into statements (e.g., "... is female.") issued by the user and added to the knowledge base, taking them out of the list of items which lack information. In contrast to BetterRelations, such input methods typically do not contain any means of filtering (possibly intentional) disruptive user input and do not provide edge weights.

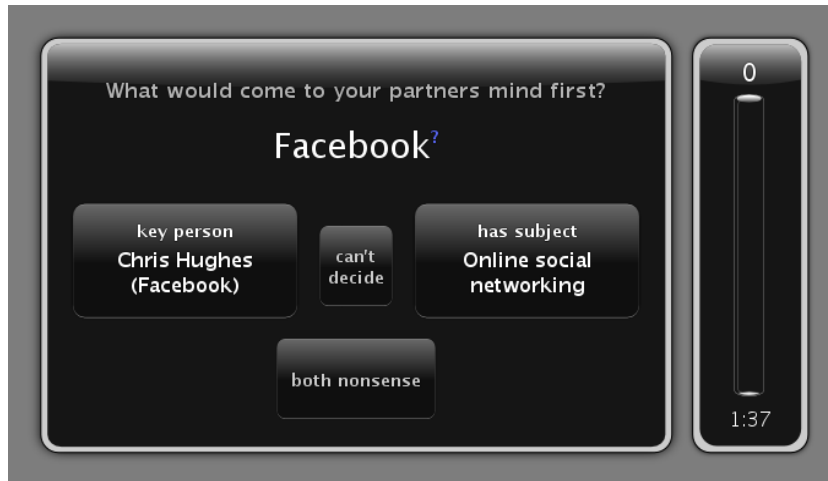
### 3 The Game

A straightforward approach to collect association strengths for Linked Data triples is this: First, we select a Linked Data resource of interest (e.g., dbpedia:

<sup>6</sup> <http://www.freebase.com/>

<sup>7</sup> <http://typewriter.freebaseapps.com/>

<sup>8</sup> <http://genderizer.freebaseapps.com/>



**Fig. 1.** In a game round, choosing phase.

Facebook or `dbpedia:Wiki`). We call this a *topic of interest* or simply *topic*. We then show randomly shuffled lists of all related triples to test persons and ask them to order the triples by decreasing importance. In the context of this work, given a topic, we define *related triples* to be the collection of (subject, predicate, object)-triples where the topic is the subject.<sup>9</sup>

The aforementioned approach suffers from the problem that the outcome of each of these experiments, which is a user centric ranking, is not only highly subjective, but sometimes even unstable for one person over time. In order to overcome difficulties for humans when sorting lengthy lists, we could ask for the atomic relative comparisons of two facts about one topic and then use an objective rating algorithm to generate an absolute ranking of the topic's related facts. This leads us to the idea behind BetterRelations.

### 3.1 BetterRelations

*BetterRelations*<sup>10</sup> is a symmetric two player output (decision) agreement game in terms of von Ahn and Dabbish's design principles for Games With A Purpose [5]:

A player starting to play the game is randomly matched with some other player for a predefined timespan (e.g., 2 minutes). In every round (see Figure 1) both players are presented with a *topic*, which actually is a Linked Data resource's symbol (e.g., *Facebook*, the symbol for `dbpedia:Facebook`), and two *items*, which are symbolic forms of facts about the topic (e.g., *key person Chris*

<sup>9</sup> Extending the list by triples where the topic is the object (incoming links) typically imports a large number of unimportant facts for the topic (e.g., in Wikipedia and thus in DBpedia one would expect to learn about Facebook by visiting the page about it, not by reading through all the pages linking to its page).

<sup>10</sup> BetterRelations can be played online: <http://lodgames.k1.dfki.de>

*Hughes (Facebook)* and *has subject Online social networking*). As in Matchin the facts are presented to the players in randomized order to counter easy cheating attempts.

Both players are asked to select the fact that their partner will have thought of first. In case a player does not know the topic, a quick info can be requested by clicking on the question mark appended to the topic. Doing so will internally mark the player’s decision as influenced and the partner’s as unvalidated. To decide, each player can either click on the more important fact’s button or on two additional buttons in case the player can’t decide between the alternatives or thinks that both alternatives are nonsense / noise.

As in Matchin, BetterRelations rewards agreements between both players with points and punishes disagreements without subtracting points, in order to increase game fun. The scoring function bases on the number of successive agreements in the current and preceding rounds: Players are rewarded with 0, 5, 10, 25, 50, 75, 90, 95, 98, 99, 99, 99, 100, . . . , 100 additional points for a streak of 0, 1, 2, 3, . . . agreements. In contrast to Matchin (where the streak is reset to 0 on a mismatch), in BetterRelations a mismatch will only decrease the streak by 2 and does not reward the current round with additional points.

BetterRelations includes two more buttons: “can’t decide” and “both nonsense” than Matchin. Hence, the scoring function was changed in order to counter easy cheating strategies such as always selecting the “can’t decide” button. In terms of the scoring function the both middle buttons are the same button (it counts as an agreement if one player selects “can’t decide” and the other “both nonsense”) and an agreement on the middle buttons will not be rewarded with additional point, but instead will sustain the accumulated streak. Furthermore, a player who requested a quick info will not be rewarded with points in the current round.

On the server side the game records a large amount of relative decisions between pairs of items, filtered by a partner and uses them to upgrade ratings in case of agreements. A both nonsense agreement will mark both items as nonsense and exclude them from future games. Generating an absolute ranking from such results can be compared to chess rating systems, where based on the outcomes of atomic competitions (player  $p_1$  won against  $p_2$ ), a global ranking is calculated, just that in this case it is not players competing, but facts [6]. In contrast to Matchin, BetterRelations uses a TrueSkill [10] based algorithm internally to update fact ratings after each agreement, selects next fact pairs for a topic in a way to minimize the overall needed amount of decisions and stops sorting lists with  $n$  facts after  $n \cdot \log_2(n)$  updates, determined to be a good threshold by simulations.

After rewarding the players with points, the next round starts until the game runs out of time. The next topic is chosen by selecting the topic least often played by both players from a list of topics currently opened for playing, which is based on the topmost accessed Wikipedia articles. In the end, both players see a summary of their performance showing the amount of points gained in this game, the longest streak and their total game score in BetterRelations.

In case no partner can be found or the partner leaves the Game, BetterRelations also provides a single player mode, which will either replay rounds with unvalidated decisions or replay previous two player games if no unvalidated decisions are left. As the latter replays usually waste human decisions, the single player mode can also be configured to initiate two player games with a certain probability and fake the (dis-)agreement by chance, based on the player’s historical rate of agreements. The results of such rounds again provide new unvalidated decisions used by other single players.

### 3.2 Game Data Acquisition and Preprocessing

As BetterRelations tries to rank multiple lists of triples related to one topic each, we first of all have to decide which topics we want to play. Topics should be well known to most players and be interesting, in order to receive valuable feedback and provide an entertaining game. Additionally each of the topics should have associated Linked Data triples. Hence, BetterRelations selects topics (Linked Data URIs) corresponding to the most often accessed Wikipedia pages<sup>11</sup>, which include pages such as Wiki, United States, Facebook, Google. Every time the game needs a new game topic and its related triples (e.g., because an existing topic’s facts were sorted), it loads the corresponding triples for the next topmost Wikipedia topic from a local DBpedia mirror, which also was pre-loaded with standard vocabularies such as `rdf`, `rdfs`, `foaf`.

As showing URIs to the end-users is of limited use, the users will always see `rdfs:labels` of such references. Hence, for each URI in the list of related triples of a topic, all English or non language tagged `rdfs:labels` are acquired. For URIs with multiple labels a best label is selected following a heuristic preferring language tagged literals and such which are similar to the URI’s last part if still in doubt. Triples having the same labels are merged from a game’s point of view and such with missing labels for predicate or object excluded from the game. We call this the *symbolic form* of a triple.

Finally labels and corresponding triples are excluded, which (due to long string length) don’t fit into the game’s window, end with suspicious file endings (e.g., .jpeg) or which have an object label equal to the topic’s label (“Facebook label Facebook”).

## 4 Evaluation

After the previous sections detailed the game’s concept, data acquisition and preprocessing, we will now provide a detailed evaluation of the game itself and of the generated output.

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<sup>11</sup> Stats aggregated from raw access logs, available at <http://dom.as/wikistats/>

## 4.1 The Game

First, the game’s concept and its realization are evaluated by summarizing measurements and derived estimates. Afterwards, the outcomes of a questionnaire are provided which was presented to players of the game.

**Measurements and Estimates** In the 18 day period from Jan. 12th until Jan. 30th, 2011, the game was played by 359 Users (re-identified by cookies if possible). In this timespan 1041 games were played, out of which 431 were two-player and 610 were single-player games.

The players played a total amount of 12K rounds submitting 14.7K decisions, out of which they selected 11.2K times an item, 2K times “can’t decide” and 1.5K times “both nonsense”. This led to an amount of 3.8K mismatches, 4.7K matches, including 3.8K item matches, and 840 non item matches.

The total amount of time all players together played the game was 42 hours (rounds without any decisions were not counted, they summed up to 5 hours, 46 minutes, e.g., idle tabs). With this, we can calculate the average time a decision takes to be 10.3 seconds. The *throughput*<sup>12</sup> of BetterRelations hence is 350 decisions per human hour of gaming. With the given numbers we can also find out the *average lifetime play*, so the time an average player plays the game, to be about 7 minutes. Multiplication of both numbers gives us an *expected contribution* of 41 decisions per human.

Repeating the above for matches instead of decisions yields a *throughput* of 112 matches per human hour of gaming, and an *expected contribution* of 13 matches per human.

Knowing that the top 1000 Wikipedia topics contain 56K game items, and taking into account the observed nonsense ratio of  $\frac{1}{10}$ , we can estimate that in order to sort the facts known about the top 1000 Wikipedia topic, we would need 313K matches. In terms of players, this means that with the current implementation and we would need about 23.9K players to sort the top 1000 Wikipedia topics, i.e., 24 players per topic.

**Questionnaire** Aside from these measurements and estimates, we wanted to know if the game was fun and wanted to collect feedback for possible future enhancements. For this, an online questionnaire survey was conducted among players of the game. The questionnaire was completed by 35 participants, mainly German (32) computer science students (23) or researchers (8), 31 male and 4 female.

Apart from background questions, the questionnaire consisted of a series of 5-point Likert scale items that are listed in Table 1 and comment fields asking what the participants liked, disliked and what they were missing. The summarized results in Table 1 show that most of the players were between 21 and 33 years old and had played online games before.

<sup>12</sup> For a definition of throughput, average lifetime play and expected contribution also see [5].

The main result from the conducted survey is that the game in its current version is of limited fun and that the majority of people do not plan to play it again. From the collected numerical data we can also see that in average the participants did not know all the topics and knew even less of the game items. At the same time most of the participants agreed that the game contained too much nonsense and too many irrelevant facts.

Apart from these numerical results, a view of the collected comments yields many common aspects. Many users mentioned that they liked the idea of creating a game to collect scientific data and the design of the game. In accordance with the numerical results, most users mentioned that they disliked the high amount of nonsense, consisting for example of unknown or cryptic abbreviations. Many participants also mentioned that they disliked the formatting of dates and often were confronted with facts they did not know anything about. Some of the participants also disliked the waiting period in the beginning of the game and complained about the mixture of German and English facts.

Many of the participants also mentioned that they were missing a button “I don’t know any of these” or an initial selection of own interests, so they were not asked things they did not know that often. Many users requested a way to know who they were playing with and even suggested to make it possible to explicitly select a partner to play with. Some of the participants also suggested showing a highscore screen at the end of the game and including user accounts to save their own score and a recap phase after the game listing the questions and selected answers, showing their outcomes and providing more exploratory features.

## 4.2 Output Quality

Besides evaluating the game itself, the quality of generated results is of special interest in this work. As mentioned in the previous sections, the game calculates rating scores for the facts in each of the topics’ related triples lists. The rating score can be used to order each of these lists, generating ordered output rankings. In the testing period, the game completed the generation of 12 such lists ordered by importance ratings.

Statement	$\mu$	$\sigma$
<i>The gaming principle was easy</i>	4.43	0.77
<i>I knew all topics</i>	3.11	1.04
<i>I knew all items</i>	2.54	0.91
<i>Too much nonsense</i>	3.68	1.23
<i>Too many irrelevant facts</i>	3.57	1.13
<i>The game was fun</i>	2.66	1.04
<i>I will play it again</i>	2.34	1.29
<i>Played online games before</i>	4.20	1.33
Age	27.68	6.76

**Table 1.** Results of an online survey answered by 35 game players. Except from *Age* users could select answers from a 5-point Likert scale: 1 (Strongly disagree), 2 (Disagree), 3 (Neutral), 4 (Agree), 5 (Strongly agree).



rank	sum	ns	predicate	object	rating	ns	predicate	object
0.0	14.0		has subject	Wikis	19.41		has subject	Self-organization
1.0	26.0		has subject	Social information processing	18.33		has subject	Social information processing
2.0	28.0		has subject	Self-organization	15.78		has subject	Human-computer interaction
3.0	30.0		has subject	Hypertext	9.15		has subject	Wikis
4.0	42.5		has subject	Human-computer interaction	5.34		has subject	Hypertext
5.0	47.5		has subject	Internet history	-1.63		has subject	Internet history
6.5	74.0	x	Jahr	2007	4.24	x	Jahr	2007
6.5	74.0	x	tag	10	4.21	x	tag	10

**Table 2.** Example: Gold Standard (left) and Game Output (right) lists for topic *Wiki*. In this case *predicate* and *object* are the symbolic forms of the corresponding triples from DBpedia.

In order to assess the quality of these lists, a Gold Standard list was generated for each of these 12 topics.

The Gold Standard lists were generated by a test group consisting of 11 people who had played the game before. Each candidate was asked to manually sort each of the 12 randomly shuffled lists of related facts by importance after excluding facts that the candidate identified as nonsense. For each of the topics the manually sorted lists were aggregated by summing up the ranks for each fact and afterwards sorting ascending by rank sum, forming the Gold Standard list. In this process nonsense facts were appended to each list’s end and given a rank according to the barycenter of all nonsense items in that list. In the aggregated list a fact is said to be nonsense if the majority of test persons considered it as nonsense. An example of such a manually generated Gold Standard list can be seen in Table 2 (left).

Once a Gold Standard list is generated, the Mean Squared Errors (MSE) can be calculated for each of the individual manually generated ranked lists. The MSE is computed as the average sum of squared rank differences of each fact in the list and can be seen as blue histogram bars in Figure 2.

Calculating the average of these MSEs (so the average error an individual human makes when compared to the Gold Standard) and the deviation thereof (seen as red dashed and dotted lines in Figure 2), we can compare the human results with the game’s result (which is shown as green vertical bar).

Even though the statistics in Figure 2 should be handled carefully because of the low sample size, we can observe that the game’s result are within the  $1\sigma$  interval of manually created lists in 9 out of 12 cases. In 3 cases (*ISBN*, *Halloween* and *Harry Potter*), the game results are a bit worse than those generated by our test group, in 6 cases better than an average individual human.

After this description of the game’s evaluation and its generated output rankings, the results will be discussed in the next section.

## 5 Discussion

One of the main concerns when designing BetterRelations was the desired high quality of its generated output ratings. This task was considerably complicated by the high amount of noise which occurs in the Linked Data triples acquired mainly from DBpedia. Nevertheless, the results of the evaluation show that the

game’s outputs are about as good as those of humans in 9 out of 12 cases and even better than an average human in half of the cases.

While a 75% success rate is satisfactory, we were also interested in the problems of the 3 remaining lists, which correspond to topics *Harry Potter*, *ISBN* and *Halloween*.

An investigation of the topic *Harry Potter* revealed that while the game item ((p,o) pair) “image caption · Complete set of the seven books” was marked as nonsense in the Gold Standard list, it is ranked as top item by the game, indicating that many players preferred it over other game items. A possible explanation for this is that players of the game had limited time for their decisions and maybe overlooked the erroneous predicate label in a rush, and their association was likely dominated by the more prominent and very useful object label. At the same time, the participants of our Gold Standard test group had no time restriction to select items they regarded as nonsense. This single misplaced item accounts for a large amount of the game’s calculated MSE ( $\approx 15$ ), probably making the result much worse than it is. In the results of *Halloween* we noticed that the facts “has subject · Irish folklore”, “has subject · Irish culture” and “has subject · Scottish folklore” were marked to be nonsense in the game results. Nevertheless, these game items receive suspiciously high ratings for nonsense items which, if they were not reordered to the end of the list as done in each of the human-generated lists, would have caused a much lower MSE value. Hence, we suggest to trigger a review in cases of such discrepancies between current rating and nonsense flagging in future versions. In the third of these lists for topic *ISBN*, we could not identify an obvious reason for the discrepancy.

But even when taking these considerations into account, we are confident that the game—already in its current version—generates good output ratings from pairwise comparisons of items. Nevertheless, it remains part of future work to conduct a survey showing the game outcomes to a test group and asking for immediate feedback about the generated ranking.

Aside from the high quality of the generated ratings, we also evaluated the game itself. The the questionnaire reveals that game principle was easy and straightforward and the majority of topics was known. However, problems related to fun and replay-ability were also mentioned. An investigation of the given comments revealed that the primarily impairing factors were the presence of many cryptic abbreviations, *strange* formatting of numbers and dates, and the mixture of English and German facts. Since improvements of the game’s fun factor would further decrease the amount of 24 players needed to sort the facts known about one Wikipedia topic, we performed an analysis on the reported problems. It turned out that many of them originated from errors in the DBpedia 3.5.1 dataset, e.g., German labels which had missing or incorrect language tags, and have been resolved in the more recent DBpedia 3.6. We expect that upcoming releases of the DBpedia dataset will address even more of these problems, as the extraction mappings are improving. Such an enhanced quality of the underlying datasets has the dual effect of reducing the amount of (erroneous) triples to sort and at the same time increasing the fun of the game.

## 6 Conclusion & Outlook

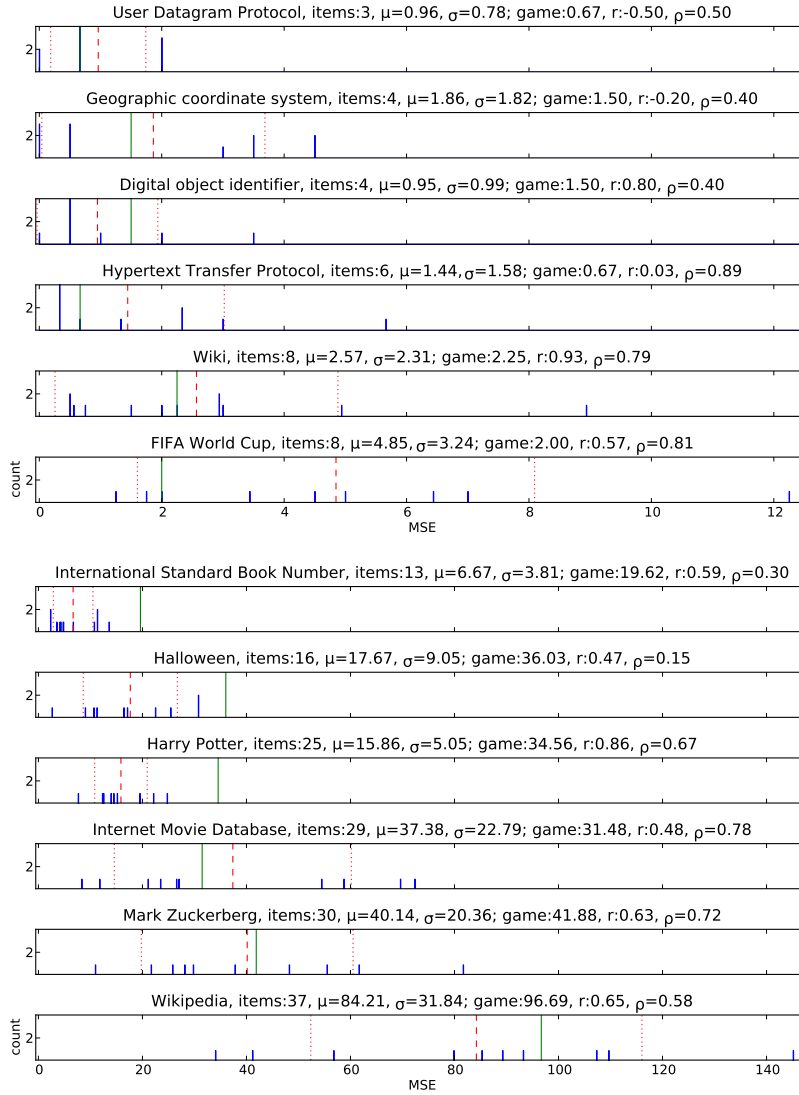
In this paper we presented a detailed evaluation of our first implementation of BetterRelations, a game with a purpose, which rates Linked Data triples by importance.

Our evaluation shows very promising results in terms of the desired quality of the generated collection of importance ratings. We believe that this approach can be used to successfully sort Linked Data triples. While the low average lifetime play indicates a problem with the game's motivation, this appears to be mainly caused by the high amount of noise in the underlying Linked Data triples. As even slight improvements of the average lifetime play could already drastically reduce the number of players needed to sort the facts known about a popular Wikipedia topic, our future work will focus on methods to detect noise and the way how the game deals with it. We also plan to provide the game's output (ranked lists with rating scores) as Linked Data, allowing others to rank result sets of queries by importance for humans, and implement other ways to increase the player's fun, such as user accounts and high scores.

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**Fig. 2.** Comparison of Gold Standard and game output on 12 topics' item lists. Blue histogram bars show the MSEs of each manually generated lists, their mean  $\mu$  is shown as a red dashed line, their standard deviation  $\sigma$  as red dotted lines. The game's MSE error is shown as a green line. The titles also include the Pearson product-moment correlation coefficient  $r$  and Spearman's rank correlation coefficient  $\rho$  of the Gold Standard List and the game's output.