Graded Relevance Assessments and Graded Relevance Measures of NTCIR: A Survey of the First Twenty Years

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Abstract NTCIR was the first large-scale IR evaluation conference to construct test collections with graded relevance assessments: the NTCIR-1 test collections from 1998 already featured relevant and partially relevant documents. In this paper, I first describe a few graded-relevance measures that originated from NTCIR (and a few variants) which are used across different NTCIR tasks. I then provide a survey on the use of graded relevance assessments and of graded relevance measures in the past NTCIR tasks which primarily tackled ranked retrieval. My survey shows that the majority of the past tasks fully utilised graded relevance by means of graded evaluation measures, but not all of them; interestingly, even a few relatively recent tasks chose to adhere to binary relevance measures. I conclude this paper by a summary of my survey in table form, and a brief discussion on what may lie beyond graded relevance.

1 Introduction

The evolution of NTCIR is quite different from that of TREC when it comes to how relevance assessments have been conducted and utilised. In 1992, TREC started off with a high-recall task (i.e., the adhoc track), with binary relevance assessments (Harman 2005, p. 34):

Relevance was defined within the task of the information analyst, with TREC assessors instructed to judge a document relevant if information from that document would be used in some manner for the writing of a report on the subject of the topic. This also implies the use of binary relevance judgments; that is, a document either contains useful information and is therefore relevant, or it does not.
Moreover, early TREC tracks heavily relied on evaluation measures based on binary relevance, such as **11-point Average Precision**, **R-precision**, and (noninterpolated) **Average Precision** (Buckley and Voorhees, 2005), which meant, for example, that **highly** relevant documents and **marginally** relevant documents (Sormunen, 2002) were treated as if they were equally valuable. It was in the TREC 2000 (a.k.a. TREC-9) Main Web task that **3-point graded** relevance assessments were introduced, based on feedback from web search engine companies at that time (Hawking and Craswell, 2005, p. 204). Accordingly, this task also adopted **Discounted Cumulative Gain (DCG)**, proposed at SIGIR 2000 (Jarvelin and Kekalainen, 2000), to utilise the graded relevance assessments.

NTCIR has collected graded relevance assessments from the very beginning: the NTCIR-1 test collections from 1998 already featured **relevant** and **partially relevant** documents (Kando et al., 1999). Thus, while NTCIR borrowed many ideas from TREC when it was launched in the late 1990s, its policy regarding relevance assessments seems to have followed the paths of Cranfield II (which had 5-point relevance levels) (Cleverdon et al., 1966, p. 21), Oregon Health Sciences University’s MEDLINE Data Collection (OHSUMED) (which had 3-point relevance levels) (Hersh et al., 1994), as well as the first Japanese IR test collections BMIR-J1 and BMIR-J2 (which also had 3-point relevance levels) (Sakai et al., 1999).

Interestingly, with perhaps a notable exception of the aforementioned TREC 2000 Main Web Task, it is true for both TREC and NTCIR that the introduction of graded relevance assessments did not necessarily mean immediate adoption of evaluation measures that can utilise graded relevance. For example, although the TREC 2000 filtering track (Robertson and Hull, 2001) reused the aforementioned OHSUMED collection, its evaluation measures were based on binary relevance; while the TREC 2003-2005 robust tracks constructed adhoc IR test collections with 3-point scale graded relevance assessments, they adhered to binary-relevance measures such as **Average Precision (AP)** (Voorhees, 2006). Similarly, as I shall discuss in this paper, while almost all of the past IR tasks of NTCIR had graded relevance assessments, not all of them fully utilised them by means of graded-relevance measures. This is the case despite the fact that a graded-relevance measure called the **normalized sliding ratio** (NSR) was proposed in 1968 (Pollock, 1968), and was discussed in an 1997 book by Korthag (1997), along with another graded-relevance measure that is based on user satisfaction and frustration. NSR is actually what is now known as **normalized (nondiscounted) cumulative gain (nCG)**.

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1 A highly relevant document document was considered to be worth 100 times as much as a relevant one. Natural logarithm was used as the patience parameter $b$ for discounting.

2 Korthag (1997, p. 209) suggests that the ideal list (which Pollock calls the **master list**) of NSR is obtained by reordering the top $k$ documents of a given system output, and Jarvelin and Kekalainen (2002, p.426) argue that this is different from the ideal list for normalised (discounted) cumulative gain (nDCG). However, Korthag’s example is not accurate, for Pollock (1968) defines his master list as “a listing of all documents in the library [...] as being ordered in decreasing master value.” That is, his master list is exactly the ideal list of nDCG, and therefore his NSR is exactly nCG. However, this measure is a set retrieval measure; unlike nDCG, it is not adequate as a ranked retrieval measure. See Section 2.1.3 for the formal definition of NSR / nCG.
Section 2 briefly describes a few graded-relevance measures that originated from NTCIR and have been used in several NTCIR tasks. Section 3 provides an overview of past ranked retrieval tasks of NTCIR that adhered to binary-relevance measures despite having graded relevance assessments. Section 4 provides an overview of past ranked retrieval tasks of NTCIR that utilized graded-relevance measures. Finally, Section 5 summarizes the above survey in table form, and discusses what may lie beyond evaluation based on graded relevance.

It should be noted that the present survey covers only NTCIR tasks that are primarily ranked retrieval and involve graded relevance assessments: Primarily NLP-oriented tasks such as summarisation and question answering are outside the scope; also, Crosslingual Link Discovery (Tang et al, 2013) is not discussed here as the task did not have any graded relevance assessments although it did involve ranked retrieval.

2 A Few Graded Relevance Measures Used across NTCIR Tasks

2.1 Q-measure for Adhoc IR, and its Variants

This section briefly describes the Q-measure (or just “Q” for short) and its variants. All of them are graded-relevance measures for ad hoc IR. The measures discussed in this section can be computed using NTCIREVAL or its predecessor ir4qa_eval (Sakai et al, 2008).

2.1.1 Q-measure

The Q-measure bears its name because it was originally designed for evaluating a ranked list of answers for a given question, where multiple correct answer strings could form an equivalence class (Sakai, 2004). For example, for a question “Who were the members of The Beatles?” a gold equivalence class could contain “Ringo Starr” (highly relevant) and “Richard Starkey” (partially relevant). If both of the above answer strings are included in the same ranked list of answers, then only one of them is treated as relevant. However, for document retrieval where we have document IDs instead of arbitrary answer strings, the notion of equivalence class disappears. In this situation, Q is actually a generalised form of AP, as explained below.

Given a graded-relevance test collection, we follow the approach of nDCG and first decide on the gain value $g_{v_x}$ for each relevance level $x$; for $x = 0$ (nonrelevant),

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1. [http://research.nii.ac.jp/ntcir/tools/ntcireval-en.html](http://research.nii.ac.jp/ntcir/tools/ntcireval-en.html)
2. [http://research.nii.ac.jp/ntcir/tools/ir4qa_eval-en.html](http://research.nii.ac.jp/ntcir/tools/ir4qa_eval-en.html)
3. A similar idea was used earlier in the NTCIR-3 Web Retrieval task (Eguchi et al, 2003), where retrieving duplicate web pages was penalised (See Section 4.1).
we let $g_{v_0} = 0$. For a given ranked list of documents for a particular topic, we let the gain at rank $r$ be $g(r) = g_{v_x}$ if the document at $r$ is $x$-relevant. Moreover, for this topic, we consider an ideal ranked list, obtained by listing up all known $x$-relevant ($x > 0$) documents in decreasing order of $x$; we denote the gain at rank $r$ in this ideal list by $g^*(r)$. Let the cumulative gain at rank $r$ of the system output be $cg(r) = \sum_{i=1}^{r} g(i)$; similarly, let $cg^*(r) = \sum_{i=1}^{r} g^*(i)$. Note that nCG (i.e., NSR) at cutoff $l$ is exactly $cg(l)/cg^*(l)$. However, this measure is not adequate as a ranked retrieval measure, since the ranks of the retrieved relevant documents within top $l$ do not matter.

Let the total number of relevant documents (i.e., $x$-relevant where $x > 0$) for the topic be $R$. Let $I(r)$ be a flag, which equals zero if the document at $r$ is nonrelevant and one otherwise. Then $C(r) = \sum_{i=1}^{r} I(i)$ is the number of relevant documents between ranks 1-$r$. The Q-measure is defined as
\[ Q = \frac{1}{R} \sum_{r} R \cdot I(r) \cdot BR(r) , \]  
(1)
where $BR(r)$ is the blended ratio given by
\[ BR(r) = \frac{C(r) + \beta cg(r)}{r + \beta cg^*(r)} . \]  
(2)
Here, $\beta$ is the patience parameter which is usually set to one; its significance is discussed in Sakai (2014). Note that $C(r)/r$ represents binary Precision at rank $r$; hence, both Precision and nCG are embedded in Eq. (2) Moreover, note that letting $\beta = 0$ reduces $Q$ to AP.

Just as nDCG penalises relevant documents retrieved at low ranks by means of discounting the gain values, $Q$ achieves a similar effect by means of the $r$ in the denominator of Eq. (2); see Sakai (2014) for details. $Q$ and nDCG behave quite similarly; see, for example, Sakai (2006a) and Sakai (2007a). For a comparison of $Q$ and Graded Average Precision (Robertson et al, 2010), see Sakai and Song (2011); for a comparison of $Q$ and Generalised Average Precision (Kishida, 2005), see Sakai (2007b).

For small document cutoffs (e.g., evaluating the top 10 URLs in a Search Engine Result Page (SERP)), the following cutoff-based $Q$ may also be used, to ensure the $[0,1]$ range:
\[ Q@l = \frac{1}{\min(l,R)} \sum_{r} l \cdot I(r) \cdot BR(r) , \]  
(3)
where $l$ is the cutoff value.

As we shall discuss later, $Q$ was used in the following NTCIR ranked retrieval tasks: CLIR (Kishida et al, 2007), IR4QA (Sakai et al, 2008, 2010b), Geo-Time (Gey et al, 2010, 2011), CQA (Sakai et al, 2010b), Temporalia (Joho et al, 2011).

\[ 6 \text{ Note that if } R > l, Q \text{ as defined by Eq. (1) would be smaller than 1 even for an ideal list.} \]
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2014), WWW [Luo et al, 2017; Mao et al, 2019], OpenLiveQ [Kato et al, 2017, 2019], and CENTRE [Sakai et al, 2019].

2.1.2 Variants

Just like AP and nDCG, Q is more suitable for topics with informational intents than navigational ones (Broder, 2002): retrieving many relevant documents is rewarded. On the other hand, \( P^+ \) is a variant of Q suitable for topics with navigational intents, for which just one or a few highly relevant documents are needed. As I shall discuss in Section 4.1, \( P^+ \) was used in the NTCIR-12 and -13 Short Text Conversation (STC) tasks [Shang et al, 2016, 2017].

For a given system output and a document cutoff \( l \), let \( r_p \) be the rank of the highest-ranked document among the most relevant documents within top \( l \). This is called the preferred rank, denoted by \( r_p \). The model behind \( P^+ \) assumes that no user will examine documents below rank \( r_p \). If there is no relevant document within top \( l \), then \( P^+ = 0 \). Otherwise,

\[
P^+ = \frac{1}{C(r_p)} \sum_{r} I(r) BR(r).
\]

(4)

For a comparison of \( P^+ \) with other measures designed for evaluation with navigational intents such as Weighted Reciprocal Rank (WRR) [Eguchi et al, 2003], see Sakai (2007c). Section 4.1 also touches upon WRR.

Both Q and \( P^+ \) are instances of the Normalised Cumulative Utility (NCU) family [Sakai and Robertson, 2008], defined as

\[
NCU = \sum_{r=1}^{\infty} P_S(r) NU(r),
\]

(5)

Given a population of users, it is assumed that 100\( P_S(r) \)% of those users will stop and abandon the ranked list at rank \( r \) due to satisfaction; the utility of the ranked list for this particular group of users is given by \( NU(r) \). Hence, NCU is the expectation of the normalised utility over a population of users. For Q, the stopping probability \( P_S(r) \) is uniform over all relevant documents; for \( P^+ \), it is uniform over all relevant documents at or above rank \( r_p \). Both Q and \( P^+ \) use \( BR(r) \) as the utility. Chapelle et al. (Chapelle et al, 2009) point out that their Expected Reciprocal Rank (ERR) measure is also an instance of NCU: ERR’s stopping probability\(^7\) at \( r \) depends on the relevant documents seen within ranks 1-\((r-1)\), and its utility is given by the Reciprocal Rank (RR): \( 1/r \). Precision at \( l \), AP, and RR can also be regarded as instances of NCU.\(^8\)

\(^7\) Sakai and Robertson (2008) discuss a stopping probability distribution that also depends on relevant documents seen so far, which they call the rank-biased distribution.

\(^8\) Precision at \( l \) assumes that all users stop at rank \( l \); AP assumes that the stopping probability distribution is uniform over all relevant documents; RR assumes that all users stop at rank \( r_1 \), the
2.2 $D^\gamma$-measures for Diversified IR, and its Variants

This section briefly describes the $D^\gamma$-measures (Sakai and Song, 2011) and their variants. All of them are graded-relevance measures for diversified IR. While the diversified IR tasks at TREC have used $\alpha$-nDCG (Clarke et al., 2008) and intent-aware measures (Agrawal et al., 2009) (e.g. intent-aware Expected Reciprocal Rank (ERR) (Chapelle et al., 2011)) etc., the diversified IR tasks of NTCIR have used $D^\gamma$-measures and their variants as the official measures.

For diversified IR evaluation, we generally require a set of topics, and a set of intents for each topic, and the probability of intent $i$ given topic $q$ ($Pr(i|q)$), and intentwise graded relevance assessments. Note that an adhoc IR test collection may be regarded as a specialised case of a diversified IR test collection where every topic has exactly one intent $i$ such that $Pr(i|q) = 1$.

The measures discussed in this section can also be computed using NTCIREVAL (See Section 2.1).

2.2.1 $D^\gamma$-measure

A $D^\gamma$-measure (e.g., $D^\gamma$-nDCG) is defined as:

$$D^\gamma-\text{measure} = \gamma I\text{-rec} + (1 - \gamma) D\text{-measure},$$  

(6)

where I-rec is the intent recall (a.k.a., subtopic recall (Zhai et al., 2003)), i.e., the number of intents covered by the SERP for a given topic; $\gamma$ is a parameter that balances I-rec (a pure diversity measure) and D-measure (an overall relevance measure explained below), usually set to $\gamma = 0.5$.

A D-measure (e.g., D-nDCG) is a measure defined by first constructing an ideal ranked list based on the global gain for each document and then computing an adhoc IR measure (e.g., nDCG) based on the ideal list. For each document, if it is $x$-relevant to intent $i$, we give it a gain value of $gv_{i,x}$; its global gain is then computed as $\sum Pr(i|q)g_{i,x}$. A global ideal list is then obtained by sorting all documents by the global gain (in descending order). Thus, unlike intent-aware measures (Agrawal et al., 2009; Chapelle et al., 2011), a single ideal list is defined for a given topic $q$. Similarly, the system’s ranked list is also scored using the global gain: if the document at $r$ is $x$-relevant to intent $i$ (for each $i$), we let the intentwise gain value be $g_i(r) = g_{v_{i,x}}$, so that the global gain for this document is given by

$$GG(r) = \sum_i Pr(i|q)g_i(r).$$  

(7)

rank of the first relevant document in the SERP. For all these measures, the utility at $r$ is given by Precision at $r$. 

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Thus graded-relevance measures such as nDCG and Q can be computed by treating the global gain values just like traditional gain values. The resultant measures are called D-nDCG, D-Q, etc.

The principle behind the global ideal list is as follows. Let rel be a random binary variable: it can either be 1 (relevant) or 0 (nonrelevant). In diversity evaluation where we have a set of intents \( \{i\} \) for topic \( q \), we define \( \text{rel} \) to be 1 for \( (q,d) \) iff there is at least one intent \( i \) for \( q \) such that \( d \) is relevant for \( i \). Given a topic \( q \) and a set of documents \( \{d\} \), the Probability Ranking Principle (PRP) dictates that we rank the documents by \( \text{Pr}(\text{rel} = 1|q,d) \), that is, the probability that \( d \) is relevant to \( q \).

If we assume that the intents are mutually exclusive, the above can be rewritten as
\[
\sum_i \text{Pr}(i|q) \cdot \text{Pr}(\text{rel} = 1|i,d)
\]
where \( \text{Pr}(\text{rel} = 1|i,d) \) is the probability that \( d \) is relevant to \( i \). If we further assume that \( \text{Pr}(\text{rel} = 1|i,d) \) is proportional to the intentwise gain value \( g_{v,i,x} \), the sort key for defining the global ideal list becomes
\[
\sum_i \text{Pr}(i|q) \cdot g_{v,i,x}
\]
which is exactly the global gain.

As we shall discuss later, D\( \# \)-measures have been used in the following NTCIR ranked retrieval tasks: INTENT (Song et al, 2011; Sakai et al, 2013) IMine (Liu et al, 2014; Yamamoto et al, 2016), and Temporalia (Joho et al, 2016). For comparisons of D\( \# \)-measures with intent-aware measures (Agrawal et al, 2009; Chapelle et al, 2011) and \( \alpha \)-nDCG, we refer the reader to Sakai and Song (2011, 2013). Other studies that compared these different types of diversity measures or their extensions include Golbus et al (2013); Zhou et al (2013); Amigo et al (2018). D\( \# \)-measures have also been extended to handle hierarchical intents (Hu et al, 2015; Wang et al, 2018); see also Section 2.2.2.

### 2.2.2 Variants Used at NTCIR

In the NTCIR-10 INTENT-2 task (Sakai et al, 2013), each intent for a topic had not only the intent probability \( \text{Pr}(i|q) \), but also a tag indicating whether it is informational or navigational. For informational intents, retrieving more relevant documents should be rewarded; for navigational intents, this may not be a good idea. Hence, the task employed a DIN-measure (Sakai, 2012) in addition to D\( \# \)-measures. The only difference between D-measures and DIN-measures lies in how the global gain is computed for each document in the system output; the ideal list is unchanged. Let \( \{i\} \) and \( \{j\} \) denote the sets of informational and navigational intents for topic \( q \), and let \( \text{isnew}_j(r) = 1 \) if there is no document relevant to the navigational intent \( j \) between ranks 1 and \( r - 1 \), and \( \text{isnew}_j(r) = 0 \) otherwise. Then, for DIN-measures, the global gain for the document at rank \( r \) in the system output is given by
\[
GG^{\text{DIN}}(r) = \sum_i \text{Pr}(i|q) g_i(r) + \sum_j \text{isnew}_j(r) \text{Pr}(j|q) g_j(r).
\]

Thus, “redundant” relevant documents for each navigational intent are ignored. The instance of DIN-measure actually used at the task was DIN-nDCG.

\( ^9 \) DIN stands for diversification with informational and navigational intents
Also at the NTCIR-10 INTENT-2 task, an extension of the Q-measure and P+Q was used as an additional measure to handle the informational and navigational intents. For each informational intent $i$, let $Q_i@l$ be the score computed using Eq. 3 by treating only documents relevant to $i$ as relevant (i.e., intentwise $Q$); for each navigational intent $j$, let $P_j$ be the score computed using Eq. 4 by treating only documents relevant to $j$ as relevant (i.e., intentwise $P+$). The overall diversity measure, called $P+Q$ (Sakai, 2012), is given by

$$P+Q@l = \sum_i Pr(i|q)Q_i@l + \sum_j Pr(j|q)P_j^+.$$  

Note that $P+Q$ is a type of intent-aware measure; the novelty is that different measures (or actually, different stopping probability distributions) are used across different intents.

The Subtopic Mining (SM) subtask of the NTCIR-11 IMine Task (Liu et al., 2014) required systems to return three files for a given query: (a) a two-level hierarchy of subtopics; (b) a ranked list of the first-level subtopics; and (c) a ranked list of the second-level subtopics, in contrast to the SM subtask of INTENT task, which only required Output (b). Accordingly, the IMine organisers introduced the $H$-measure for the subtask:

$$H\text{-measure} = Hscore(\alpha D^{1+}\text{-measure} + (1 - \alpha) D^{2+}\text{-measure}),$$  

where $D^{1+}\text{-measure}$ is the $D^+_z$-measure score computed for Output (b), $D^{2+}\text{-measure}$ is the $D^+_z$-measure score computed for Output (c), and $Hscore$ is the fraction of second-level subtopics that are correctly assigned to their first-level subtopics, i.e., the accuracy of Output (a). The NTCIR-11 IMine Task actually computed $D^+_z$-nDCG as an instance of the $D^+_z$-measure family.

The Query Understanding (QU) subtask of the NTCIR-12 IMine-2 Task (Yamamoto et al., 2016) was similar to the previous SM subtasks, but requires systems to return a ranked list of (subtopic, vertical) pairs (e.g., (“iPhone 6 photo”, Image), (“iPhone 6 review”, Web)) for a given query. Accordingly, they used the following extension of the $D^+_z$-nDCG:

$$QU\text{score}@l = \lambda D^+_z\text{-nDCG}@l + (1 - \lambda)V\text{-score}@l,$$

where $V\text{-score}$ measures the appropriateness of the named vertical for each subtopic in the system list by leveraging $Pr(v|i)$, i.e., the importance of vertical $v$ for intent $i$. More specifically, it is given by

$$V\text{-score}@l = \frac{1}{l} \sum_{r=1}^{l} \frac{Pr(v(r)|i(r))}{\max_{v \in V} Pr(v|i(r))},$$

where $l$ is the number of subtopics in the system list.
where $V$ is the set of verticals, $v(r)$ is the vertical returned by the system at rank $r$, and $i(r)$ is the intent to which the subtopic returned at rank $r$ belongs.\textsuperscript{10}

### 3 Graded Relevance Assessments, Binary Relevance Measures

This section provides an overview of NTCIR ranked retrieval tasks that did not use graded-relevance evaluation measures even though they had graded relevance assessments.

#### 3.1 Early IR and CLIR Tasks (NTCIR-1 through -5)

The Japanese IR and (Japanese-English) crosslingual tasks of NTCIR-1 \cite{Kando1999} constructed test collections with 3-point relevance levels (relevant, partially relevant, nonrelevant), but used binary-relevance measures such as AP and R-precision\textsuperscript{11} by either treating the relevant and partially relevant documents as “relevant” or treating only the relevant documents as “relevant.” However, it should be stressed at this point that using binary-relevance measures with different relevance thresholds cannot serve as substitutes for a graded relevance measure that encourages optimisation towards an ideal ranked list (i.e., a list of documents sorted in decreasing order of relevance levels). If partially relevant documents are ignored, a SERP whose top $l$ documents are all partially relevant and one whose top $l$ documents are all nonrelevant can never be distinguished from each other; if relevant documents and partially relevant documents are all treated as relevant, a SERP whose top $l$ documents are all relevant and one whose top $l$ documents are all partially relevant can never be distinguished from each other.

The Japanese and English (monolingual and crosslingual) IR tasks of NTCIR-2 \cite{Kando2001} constructed test collections with 4-point relevance levels: S (highly relevant), A (relevant), B (partially relevant), and C (nonrelevant). However, the organisers used binary-relevance measures such as AP and R-precision by either treating only the S and A documents as relevant or treating the S, A, and B documents as relevant. As for the Chinese monolingual and Chinese-English IR tasks of NTCIR-2 \cite{Chen2001}, three judges independently judged each pooled document using 4-point relevance levels, and then a score was assigned to each relevance level. Finally, the scores were average across the three assessors. For example, if a document is judged “very relevant” (score: 1), “relevant” (score: 2/3), and “partially relevant” (score: 1/3) independently, its overall score is $(1 + 2/3 + 1/3)/3 = 2/3$. The organisers then applied two different thresholds to

\textsuperscript{10} In INTENT and IMine tasks, an \textit{intent} is derived by manually clustering a set of submitted subtopic strings. Therefore, a subtopic belongs to exactly one intent (See also Section 4.6).

\textsuperscript{11} For a topic with $R$ known relevant documents, R-precision is the precision at rank $R$, or equivalently, the recall at rank $R$. Note that this is a set retrieval measure, not a ranked retrieval one.
map the scores to binary relevance: rigid relevance was defined by treating documents with scores 2/3 or larger as relevant; relaxed relevance was defined by treating those with scores 1/3 or larger as relevant. For evaluating the runs, rigid and relaxed versions of recall-precision curves (RP curves) were used.

The NTCIR-3 CLIR (Cross-Language IR) task (Chen et al, 2002) was similar to the previous IR tasks: 4-point relevance levels (S,A,B,C) were used; rigid relevance was defined using the S and A documents while relaxed relevance was defined using the B documents in addition; finally, rigid and relaxed versions of AP were computed for each run. The NTCIR-4 and NTCIR-5 CLIR tasks (Kishida et al, 2004, 2005) adhered to the above practice.

It is worth noting that all of the above tasks used the trec_eval programme from TREC\footnote{https://trec.nist.gov/trec_eval/} to compute binary-relevance measures such as AP. At NTCIR-6, the CLIR organisers finally took up graded-relevance measures, as I shall discuss in Section 4.2.

### 3.2 Patent (NTCIR-3 through -6)

The Patent Retrieval Tasks of NTCIR, which were run from NTCIR-3 (2002) to NTCIR-6 (2007), never used graded-relevance measures despite having graded relevance assessments with highly unique properties.

The NTCIR-3 Patent Retrieval task (Iwayama et al, 2003) was a news-to-patent technical survey search task, with 4-point relevance levels: A (relevant), B (partially relevant), C (judged nonrelevant after reading the entire patent), and D (judged nonrelevant after just reading the patent title). RP curves were drawn based on strict relevance (only A treated as relevant) and relaxed relevance (A and B treated as relevant). In the overview paper, “median of the average precisions for each topic” is discussed, but systems were not compared based on AP.

The main task of the NTCIR-4 Patent Retrieval task (Fujii et al, 2004) was a patent-to-patent invalidity search task. There were two types of relevant documents:

A A patent that can invalidate a given claim on its own;
B A patent that can invalidate a given claim only when used with one or more other patents.

For example, patents $B_1$ and $B_2$ may each be nonrelevant (as they cannot invalidate a claim individually), but if they are both retrieved, the pair should serve as one relevant document. In addition, the organisers provided passage-level binary relevance assessments: if a single passage provides sufficient grounds for the patent (from which the passage was drawn) to be either A or B, that passage is relevant; if a group of passages serves the same purpose, that passage group is relevant. However, these passage-level relevance assessments were not utilised for evaluation at NTCIR-4. At the evaluation step, the organisers used AP by either treating only the
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A document as relevant (rigid evaluation) or treating both A and B documents as relevant (relaxed evaluation). Note that the above relaxed evaluation has a limitation: recall the aforementioned example with $B_1$ and $B_2$, and consider a SERP that managed to return only one of them (say $B_1$). Relaxed evaluation rewards the system for returning $B_1$, even though this document alone does not invalidate the claim.

The Document Retrieval subtask of the NTCIR-5 Patent Retrieval task [Fujii et al., 2005] was similar to its predecessor, but the relevant documents were determined purely based on whether and how they were actually used by a patent examiner to reject a patent application; no manual relevance assessments were conducted for this subtask. The graded relevance levels were defined as follows:

A A citation that was actually used on its own to reject a given patent application;
B A citation that was actually used along with another one to reject a given patent application.

As for the evaluation measure for Document Ranking, the organisers adhered to rigid and relaxed AP. In addition, the task organisers introduced a Passage Retrieval subtask by leveraging passage-level binary relevance assessments collected as in the NTCIR-4 Patent task: given a patent, systems were required to rank the passages from that same patent. As both single passages and groups of passages can potentially be relevant to the source patent (i.e., the passage(s) can serve as evidence to determine that the entire patent is relevant to a given claim), this poses a problem similar to the one discussed above with patents $B_1$ and $B_2$: for example, if two passages $p_1$, $p_2$ are relevant as a group but not individually, and if $p_1$ is ranked at $i$ and $p_2$ is ranked at $i'$ ($i' > i$), how should the SERP of passage be evaluated? To address this, the task organisers introduced a binary-relevance measure called the Combinational Relevance Score (CRS), which assumes that the user who scans the SERP must reach as far as $i'$ to view both $p_1$ and $p_2$.

The Japanese Document Retrieval subtask of the NTCIR-6 Patent Retrieval task [Fujii et al., 2007] had two different sets of graded relevance assessments; the first set (“Def0” with A and B documents) was defined in the same way as in NTCIR-5; the second set (“Def1”) was automatically derived from Def0 based on the International Patent Classification (IPC) codes as follows:

H The set of IPC subclasses for this cited patent has no overlap with that of the input patent (and therefore it is relatively difficult to retrieve this patent);
A The set of IPC subclasses for this cited patent has some overlap with that of the input patent;
B The set of IPC subclasses for this cited patent is identical to that of the input patent (and therefore it is relatively easy to retrieve this patent).

[13] In fact, AP, Q or any measure from the NCU family (See Section 2.1.2) can easily be extended to handle combinational relevance for Document Retrieval (See the above example with $(B_1, B_2)$) and for Passage Retrieval (See the above example with $(p_1, p_2)$) [Sakai, 2006b]. For example, given a SERP that contains $B_1$ at rank $i$ and $B_2$ at rank $i'$ ($i' > i$), we can assume that a group of users will abandon the ranked list at rank $i'$, that is, only after viewing both documents. Hence, for this user group, the utility (i.e., precision in the case of AP) can be computed at rank $i'$, but not at rank $i$. 

As for the English Document Retrieval subtask, the relevance levels were also automatically determined based on IPC codes, but only two types of relevant documents were identified, as each USPTO patent is given only one IPC code: A (cited patents whose IPC subclasses were not identical to those of the input patent), and B (cited patents whose IPC subclasses were identical to those of the input patent). In both subtasks, AP was computed by considering different combinations of the above relevance levels.

### 3.3 SpokenDoc/SpokenQuery&Doc (NTCIR-9 through -12)

The NTCIR-9 and NTCIR-10 SpokenDoc tasks (2011, 2013) (Akiba et al., 2011, 2013) and the NTCIR-11 and NTCIR-12 SpokenDoc&Query tasks (2014, 2016) (Akiba et al., 2014, 2016) also never used graded-relevance measures despite having graded relevance assessments. Hereafter, we omit the discussion of the Spoken Term Detection (STD) subtasks of these tasks as they did not involve graded relevance assessments.

The Spoken Document Retrieval (SDR) subtask of the NTCIR-9 SpokenDoc task had two “subsubtasks”: Lecture Retrieval and Passage Retrieval, where a passage is any sequence of consecutive inter-pausal units. Passage-level relevance assessments were obtained on a 3-point scale (relevant, partially relevant, and non-relevant), and it appears that the document-level (binary) relevance was deduced from them. AP was used for evaluating Document Retrieval, whereas variants of AP, called utterance-based (M)AP, pointwise (M)AP, and fractional (M)AP were used for evaluating Passage Retrieval. While these variants compare the system’s ranked list of passages with the gold list of passages in different ways, none of them utilise the distinction between relevant and partially relevant passages in the gold data; they are binary-relevance measures. The NTCIR-10 SpokenDoc-2 Spoken Content Retrieval (SCR) subtask (Akiba et al., 2013) was similar to the SDR subtask at NTCIR-9, with Lecture Retrieval and Passage Retrieval subsubtasks. Lecture Retrieval used a revised version of the NTCIR-9 SpokenDoc topic set, and its gold data does not contain graded relevance assessments; binary-relevance AP was used for the evaluation. As for Passage Retrieval, a new topic set was devised, again with 3-point relevance levels. The three binary-relevance AP variants from the NTCIR-9 SDR task the evaluation was done in the same way as in NTCIR-9.

The Slide Group Segment (SGS) Retrieval subsubtask of the NTCIR-11 SpokenQuery&Doc SCR subtask involved the ranking of predefined retrieval units (i.e.,

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14 The official test collection data of the NTCIR-9 SDR task (evalsdr) contains only passage-level gold data.

15 While the fractional (M)AP considers the degree of overlap between a gold passage and a retrieved passage, whether the gold passage is relevant or partially relevant is not considered.

16 This was verified by examining in the SpokenDoc-2 test collection.

17 This was verified by examining in the SpokenDoc-2 test collection.
SGSs), unlike the Passage Retrieval subtask which allows any sequence of consecutive inter-pausal units as a retrieval unit. Three-point relevance levels were used to judge the SGSs: R (relevant), P (partially relevant), and I (nonrelevant). However, the binary AP was used for the evaluation. As for the passage-level relevance assessments, they were derived from the SGSs labelled R or P, and were considered binary; the three binary-relevance AP variants were used for this subtask once again. Segment Retrieval was continued at the NTCIR-12 SpokenQuery&Doc-2 task, again with the same 3-point relevance levels and AP as the evaluation measure.\[13]

3.4 Math/MathIR (NTCIR-10 through -12)

The NTCIR-10 and NTCIR-11 Math tasks (2013, 2014)\[14] (Aizawa et al, 2013, 2014) and the NTCIR-12 MathIR task (2016) (Zanibbi et al, 2016) also adhered to binary-relevance measures despite having graded relevance assessments.

In the Math Retrieval subtask of the NTCIR-10 Math Task, retrieved mathematical formulae were judged on a 3-point scale (relevant, partially relevant, nonrelevant). Up to two assessors judged each formula, and initially 5-point relevance scores were devised based on the results. For example, for formulae judged by one assessor, they were given 4 points if the judged label was relevant; for those judged by two assessors, they were given 4 points if both of them gave them the relevant label. Finally, the scores were mapped to a 3-point scale: Documents with scores 4 or 3 were treated as relevant; those with 2 or 1 were treated as partially relevant; those with 0 were treated as nonrelevant. However, at the evaluation step, only binary-relevance measures such as AP and Precision were computed using trec_eval. Similarly, in the Math Retrieval subtask of the NTCIR-11 Math Task, two assessors independently judged each retrieved unit on a 3-point scale, and the final relevance levels were also on a 3-point scale. If the two assessor labels were relevant/relevant or relevant/partially-relevant, the final grade was relevant; if the two labels were both nonrelevant, the final grade was nonrelevant; the other combinations were considered partially relevant. As for the evaluation measures, bpref (Buckley and Voorhees, 2004; Sakai, 2007a; Sakai and Kando, 2008) was computed along with AP and Precision, using trec_eval.

The NTCIR-12 MathIR task was similar to the Math Retrieval subtask of the aforementioned Math tasks. Up to four assessors judged each retrieved unit using a 3-point scale, and the individual labels were consolidated to form the final 3-point scale assessments. As for the evaluation, only Precision (computed at several cutoffs) was used using trec_eval.

The following remarks from the Math and MathIR overview papers may be noteworthy:

\[13] The NTCIR-12 SpokenQuery&Doc-2 overview paper does not discuss the evaluation of Passage Retrieval runs.
Since the trec eval tool only accepts binary relevance judgments, the scores of evaluators were first converted into a combined relevance score [...] (Zanibbi et al, 2016).

This suggests that one reason for adhering to binary-relevance measures is that an existing tool lacked the capability to handle graded relevance. On the other hand, this may not be the only reason: in the MathIR overview paper, it is reported that the organisers chose Precision (a set retrieval measure, not a ranked retrieval measure) because it is "simple to understand" (Zanibbi et al, 2016). Thus, some researchers indeed choose to focus on evaluation with binary-relevance measures, even in the NTCIR community where we have graded relevance data by default and a tool for computing graded relevance measures is known.\footnote{NTCIREVAL has been available on the NTCIR website since 2010; its predecessor ir4qa_eval was released in 2008 (Sakai et al, 2008). Note also that TREC 2010 released \url{https://trec.nist.gov/data/web/10/gdeval.pl} for computing Normalized Discounted Cumulative Gain ($\text{nDCG}$) and ERR.}

## 4 Graded Relevance Assessments, Graded Relevance Measures

This section provides an overview of NTCIR ranked retrieval tasks that employed graded-relevance evaluation measures to fully enjoy the benefit of having graded relevance assessments.

### 4.1 Web (NTCIR-3 through -5)

The NTCIR-3 Web Retrieval task (Eguchi et al, 2003) was the first NTCIR task to use a graded relevance evaluation measure namely, DCG\footnote{This was the DCG as originally defined by Järvelin and Kekäläinen (2000) with the logarithm base $b = 2$, which means that gain discounting is not applied to documents at ranks 1 and 2. That is, a SERP that has a relevant document at rank 1 and one that has the same document at rank 2 are considered equally effective according to this measure. See also Section 4.3.}. Four-point relevance levels were used: highly relevant, fairly relevant, partially relevant, and nonrelevant. In addition, assessors chose a very small number of “best” documents from the pools. To compute DCG, two different gain value settings were used:

- **Rigid**: 3 for highly relevant, 2 for fairly relevant, 0 otherwise;
- **Relaxed**: 3 for highly relevant, 2 for fairly relevant, 1 for partially relevant, 0 otherwise.

The organisers of the Web Retrieval task also defined a graded-relevance evaluation measure called WRR (first mentioned in Section 2.1.2), designed for navigational searches (which were called Target Retrieval in the Web task). WRR is an extension...
Graded Relevance Assessments and Graded Relevance Measures of NTCIR

of the RR measure, and assumes, for example, that having a marginally relevant document at rank 1 is more important than having a highly relevant one at rank 2. However, what was actually used in the task was the binary-relevance RR, with two different thresholds for mapping the 4-point relevance levels into binary. Therefore, this measure will be denoted “(W)RR” hereafter whenever graded relevance is not utilised. Other binary-relevance measures including AP and R-precision were also used in this task. For a comparison of evaluation measures designed for navigational intents, including RR, WRR, and the aforementioned P+, we refer the reader to Sakai (2007c).

The NTCIR-14 WEB Informatinal Retrieval Task (Eguchi et al, 2004) was similar to its predecessor, with 4-point relevance levels; the evaluation measures were DCG, (W)RR, Precision etc. On the other hand, the NTCIR-14 WEB Navigational Retrieval Task (Oyama et al, 2004), used 3-point relevance levels: A (relevant), B (partially relevant), and D (nonrelevant); the evaluation measures were DCG and (W)RR, and two gain values settings for DCG were used: \((A, B, D) = (3, 0, 0)\) and \((A, B, D) = (3, 2, 0)\). Also at NTCIR-4, an evaluation measure for web search called the User’s Character Score (UCS) was proposed (Ohtsuka et al, 2004), which basically assumes that having relevant documents at consecutive ranks is better than having them alternately with nonrelevant ones. However, this is a binary-relevance measure: the proposers argue that not requiring graded relevance assessments is an advantage.

The NTCIR-15 WEB task ran the Navigational Retrieval subtask, which is basically the same as its predecessor, with 3-point relevance levels and DCG and (W)RR. For computing DCG, three gain value settings were used: \((A, B, D) = (3, 0, 0)\), \((A, B, D) = (3, 2, 0)\), and \((A, B, D) = (3, 3, 0)\). Note that the first and the third settings reduce DCG to binary-relevance measures.

4.2 CLIR (NTCIR-6)

At the NTCIR-6 CLIR task, 4-point relevance levels \((S, A, B, C)\) were used and rigid and relaxed AP scores were computed using trec_eval as before. In addition, the organisers computed “as a trial” (Kishida et al, 2007) the following graded-relevance measures using their own script: nDCG (as defined originally by Järvelin and Kekäläinen (2002)), Q-measure, and Kishida’s generalised AP (Kishida, 2005). See Sakai (2007b) for a comparison of these three graded-relevance measures. The CLIR organisers developed a programme to compute these graded-relevance measures, with the gain value setting: \((S, A, B, C) = (3, 2, 1, 0)\).
4.3 ACLIA IR4QA (NTCIR-7 and -8)

At the NTCIR-7 Information Retrieval for Question Answering (IR4QA) task (Sakai et al., 2008), a predecessor of NTCIREVAL called ir4qa_eval was released (See Section 2.1). This tool was used to compute the Q-measure, the “Microsoft version” of nDCG (Burges et al., 2005), as well as the binary-relevance AP. Microsoft nDCG (called MSnDCG in NTCIREVAL) fixes a problem with the original nDCG (See also Section 4.1): in the original nDCG, if the logarithm base is set to (say) $b = 10$, then discounting is not applied from ranks 1 to 10, and therefore nDCG at cutoff $l = 10$ is reduced to nCG (i.e., NSR; See Section 2.1.1) at $l = 10$. This is a set retrieval measure rather than a ranked retrieval measure; the ranks of the relevant documents within top 10 do not matter. Microsoft nDCG avoids this problem by using $1 / \log(1 + r)$ as the discount factor for every rank $r$, but thereby loses the patience parameter $b$ (Sakai, 2014). The relevance levels used were: L2 (relevant), L1 (partially relevant), and L0 (nonrelevant); A linear gain value setting was used: $(L_2, L_1, L_0) = (2, 1, 0)$. The NTCIR-8 IR4QA task (Sakai et al., 2010b) used the same evaluation methodology as above.

4.4 GeoTime (NTCIR-8 and -9)

The NTCIR-8 GeoTime task (Gey et al., 2010), which dealt with adhoc IR given “when and where”-type topics, constructed test collections with the following graded relevance levels:

- Fully relevant The document answers both the “when” and “where” aspects of the topic;
- Partially relevant – where The document only answers the “where” aspect of the topic;
- Partially relevant – when The document only answers the “when” aspect of the topic.

The evaluation tools from the IR4QA task were used to compute (Microsoft) nDCG, Q, and AP, with a gain value of 2 for each fully relevant document and a gain value of 1 for each partially relevant one (regardless of “when” or “where”) for the two graded-relevance measures. The NTCIR-9 GeoTime task (Gey et al., 2011) used the same evaluation methodology as above.

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21 Järvelin et al. (2008) describe another version of nDCG to fix the problem with the original nDCG.
22 D♯-nDCG implemented in NTCIREVAL also builds on the Microsoft version of nDCG, not the original nDCG.
23 While the GeoTime overview paper suggests that the above relevance levels were mapped to binary relevance, this was in fact not the case: it was the present author who conducted the official evaluation for both NTCIR-8 IR4QA and GeoTime; they were done in exactly the same way, by utilising the 3-point relevance levels.
4.5 CQA (NTCIR-8)

The NTCIR-8 Community Question Answering (CQA) task (Sakai et al., 2010a) was an answer ranking task: given a question from Yahoo! Chiebukuro (Japanese Yahoo! Answers) and the answers posted in response to that question, rank the answers by answer quality. While the Best Answers (BAs) selected by the actual questioners were already available in the Chiebukuro data, additional graded relevance assessments were obtained offline to find Good Answers (GAs), by letting four assessors independently judge each posted answer. Each assessor labeled an answer as either A (high-quality), B (medium-quality), or C (low-quality), and hence 15 different label patterns were obtained: AAAAA, AAAB, ..., BCCC, CCCC. In the official evaluation at NTCIR-8, these patterns were mapped to 4-point relevance levels: for example, AAAAA and AAAB were mapped to L3-relevant, and ACCC, BCCC and CCCC were mapped to L0. In a separate study (Sakai et al., 2011), the same data were mapped to 9-point relevance levels, by giving 2 points to an A and 1 point to a B and summing up the scores for each pattern. That is, the score for AAAAA would be 8 and therefore the relevance level assigned is L8; similarly, AAAB is mapped to L7; both AABB and AACB are mapped to L6, and so on. While this is similar to the approach taken in the Chinese-English IR tasks of NTCIR-2 (Chen and Chen, 2001), recall that the NTCIR-2 task did not utilise any graded relevance measures (Section 3.1).

Using the graded Good Answers data, three graded-relevance measures were computed: normalised gain at $l = 1$ ($nG@1$), nDCG, and Q. In addition, Hit at $l = 1$ (defined as $Hit@1 = I(1)$ using the relevance flag from Section 2.1.1) was computed for both Best Answers and Good Answers data: this is a binary-relevance measure which only cares whether the top ranked item is relevant or not.

The CQA organisers also experimented with an attempt at constructing binary-relevance assessments based on the Good Answers data. For each assessor, answers that were most highly rated by that assessor among all the posted answers were identified as his/her “favourite” answers; note that they may not necessarily be rated A. Then the union of the favourite answers from all four assessors were treated as relevant. Furthermore, the best answer selected by the questioner was also added to the binary-relevance set, for the best answer was in fact the questioner’s favourite answer.

4.6 INTENT/IMine (NTCIR-9 through 12)

The NTCIR-9 INTENT task overview paper (Song et al., 2011) was the first NTCIR overview to mention the use of the NTCIREVAL tool, which can compute various graded-relevance measures for adhoc and diversified IR, including the Q-measure, $nG@1$ is often referred to as nDCG@1; however, note that neither discounting nor cumulation is applied at rank 1.
nDCG, and D Lesbian measures. D Lesbian-nDCG and its components I-rec and D Lesbian-nDCG were used as the official evaluation measures. The Document Retrieval (DR) subtask of the INTENT task had intentwise graded relevance assessments on a 5-point scale: L0 through L4. This was obtained by hiring two assessors per topic, who independently judged each document as either highly relevant or relevant.

While the Subtopic Mining (SM) subtask of the INTENT task also used D Lesbian-nDCG to evaluate ranked lists of subtopic strings, no graded relevance assessments were involved in the SM subtask since each subtopic string either belongs to an intent (i.e., a cluster of subtopic strings) or not. Hence, the SM subtask may be considered to be outside the scope of the present survey. However, there is an interesting aspect to the evaluation of the SM subtask when D Lesbian-nDCG is used, from a graded relevance point of view. Recall the definition of the global gain (Eq. 7): when the intentwise relevance assessments are binary as is the case here, the global gain is reduced to \( \sum_i \Pr(i|q) \), i.e., the sum of the intent probabilities. Furthermore, since relevant subtopic string belongs to exactly one intent in the SM subtask, the global gain of a subtopic string that belongs to intent \( i \) is given exactly by \( \Pr(i|q) \), which is estimated based on the number of votes from assessors. That is, a D-nDCG score for the SM subtask is exactly an nDCG score where each gain value is given by the probability of the intent to which the subtopic string belongs.

In both SM and DR subtasks, the trade-offs between D-nDCG (i.e., overall relevance) and I-rec (pure diversity) were visualised in the overview paper.

The NTCIR-10 INTENT task was basically the same as its predecessor, with 5-point intentwise relevance levels for the DR subtask and D Lesbian-nDCG as the primary evaluation measure. However, as the intents came with informational/navigational tags, DIN-nDCG and P+Q were also used to leverage this information (See Section 2.2.2).

The NTCIR-11 IMine task (Liu et al., 2014) was similar to the INTENT tasks, except that its SM subtask required participating systems to return a two-level hierarchy of subtopic strings. As was described in Section 2.2.2 the SM subtask was evaluated using the H-measure, which combines (a) the accuracy of the hierarchy (i.e., whether the second-level subtopics are correctly assigned to the first-level ones), (b) the D Lesbian-nDCG score based on the ranking of the first-level subtopics, and (c) the D Lesbian-nDCG score based on the ranking of the second-level subtopics. However, recall the above remark on the INTENT SM subtask: intentwise graded relevance does not come into play in this subtask. On the other hand, the IMine DR subtask was evaluated in a way similar to the INTENT DR tasks, with D Lesbian-nDCG computed based on 4-point relevance levels: highly relevant, relevant, nonrelevant, and spam. The gain value setting used was: \((2, 1, 0, 0)\)\(^{25}\).

The IMine task also introduced the TaskMine subtask, which requires systems to rank strings that represent subtasks of a given task (e.g., “take diet pills” in response to “lose weight.”) This subtask involved graded relevance assessments. Each subtask string was judged independently by two assessors from the viewpoint of whether the subtask is effective for achieving the input task. A 4-point per-assessor relevance

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\(^{25}\) Kindly confirmed by task organisers Yiqun Liu and Cheng Luo in a private email communication (March 2019).
scale was used\(^{26}\), with weights \((3, 2, 1, 0)\), and final relevance levels were given as the average of the two scores, which means that a 6-point relevance scheme was adopted. The averages were used verbatim as gain values: \((3.0, 2.5, 2.0, 1.5, 1.0, 0)\). The evaluation measure used was nDCG, but duplicates (i.e., multiple strings representing the same subtask) were not rewarded, just as in the original Q-measure (See Section 2.1.1 and the NTCIR Web tasks (Eguchi et al., 2003).

As was already discussed in Section 2.2.2, the Query Understanding (QU) subtask of the NTCIR-12 IMine-2 Task (Yamamoto et al., 2016), a successor of the previous SM subtasks of INTENT/IMine, required systems to return a ranked list of (subtopic, vertical) pairs (e.g., (“iPhone 6 photo”, Image), (“iPhone 6 review”, Web)) for a given query. The official evaluation measure, called the QU-score (Eq. 11), is a linear combination of \(D\#\)-nDCG (computed as in the INTENT SM subtasks) and the V-score (Eq. 12) which measures the appropriateness of the named vertical for each subtopic string. Despite the binary-relevance nature of the subtopic mining aspect of the QU subtask, it deserves to be discussed in the present survey because the V-score part relies on graded relevance assessments. To be more specific, the V-score relies on the probabilities \(\{Pr(v|i)\}\), for intents \(\{i\}\) and verticals \(\{v\}\), which are derived from 3-point scale relevance assessments: 2 (highly relevant), 1 (relevant), and 0 (nonrelevant). Hence the QU-score may be regarded as a graded relevance measure.

The Vertical Incorporating (VI) subtask of the NTCIR-12 IMine-2 Task (Yamamoto et al., 2016) also used a version of \(D\#\)-nDCG to allow systems to embed verticals (e.g., Vertical-News, Vertical-Image) within a ranked list of document IDs for diversified search. More specifically, the organisers replaced the intentwise gain value \(g_i(r)\) at rank \(r\) in the global gain formula (Eq. 7) with \(Pr(v(r)|i)g_i(r)\), where \(v(r)\) is the vertical type (“Web,” Vertical-News, Vertical-Image, etc.) of the document at rank \(r\), and the vertical probability given an intent is obtained from 3-point relevance assessments as described above. As for the intentwise gain value \(g_i(r)\), it was also on a 3-point scale for the Web documents: 2 for highly relevant, 1 for relevant, and 0 for nonrelevant documents. Moreover, if the document at \(r\) was a vertical, the gain value was set to 2. That is, the verticals were treated as highly relevant. In addition, the VI subtask collected topicwise relevance assessments on a 4-point scale: highly relevant, relevant, nonrelevant, and spam. The gain values used were: \((2, 1, 0, 0)\). As the subtask had a set of very clear, single-intent topics among their full topic set, Microsoft nDCG (rather than \(D\#\)-nDCG) was used for these particular topics.

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\(^{26}\) While the overview (Section 4.3) says that a 3-point scale was used, this was in fact not the case: kindly confirmed by task organiser Takehiro Yamamoto in a private email communication (March 2019).

\(^{27}\) Kindly confirmed by task organisers Yiqun Liu and Cheng Luo in a private email communication (March 2019).
4.7 RecipeSearch (NTCIR-11)

The NTCIR-11 RecipeSearch Task (Yasukawa et al., 2014) had two subtasks: Adhoc Recipe Search and Recipe Pairing. Hereafter, we shall only discuss the former, as the latter only had binary relevance assessments. While the official evaluation results of Adhoc Recipe Search was based on binary relevance, the organisers also explored evaluation based on graded relevance: they obtained graded relevance assessments on a 3-point scale (L2, L1, L0) for a subset (111 topics) of the full test topic set (500 topics). Microsoft nDCG was used to leverage the above data with a linear gain value setting, along with the binary AP and RR.

4.8 Temporalia (NTCIR-11 and -12)

The Temporal Information Retrieval (TIR) subtask of the NTCIR-11 Temporalia Task collected relevance assessments on a 3-point scale: highly relevant, relevant, and nonrelevant. Each TIR topic contained a past question, recency question, future question, and an atemporal question, in addition to the description and search date fields; participating systems were required to produce a SERP for each of the above four questions. This adhoc IR task used Precision and Microsoft nDCG as the official measures, and the Q-measure for reference.

While the Temporally Diversified Retrieval (TDR) subtask of the NTCIR-12 Temporalia-2 Task was similar to the above TIR subtask, it required systems to return a fifth SERP, which covers all of the above four temporal classes. That is, this fifth SERP is a diversified SERP, where the temporal classes can be regarded as different search intents for the same topic. The relevance assessment process followed the practice of the NTCIR-11 TIR task (with 3-point relevance levels), and the SERPs to the four questions were evaluated using nDCG. As for the diversified SERPs, they were evaluated using α-nDCG (Clarke et al., 2008) and D♯-nDCG.

A linear gain value setting was used in both of the above subtasks.

4.9 STC (NTCIR-12 through -14)

The NTCIR-12 STC task (Shang et al., 2016) was basically a response retrieval task given a tweet (or a Chinese Weibo post; both will be referred to generically as “tweet” hereafter). For both Chinese and Japanese subtasks, the response tweets were first labelled on a binary scale, for each of the following criteria:

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28 While the overview paper says that a 4-point scale was used, this was in fact not the case: kindly confirmed by task organiser Michiko Yasukawa (March 2019) in a private email communication.

29 Kindly confirmed by task organiser Hideo Joho in a private email communication (March 2019).
Coherence Does the response logically make sense as a response to the input tweet?
Topical relevance Does the topic of the response match that of the input tweet?
Context independence Is the response appropriate for the input tweet regardless of the outside context?
Non-repetitiveness Does the response contain something new, not just a simple repetition of the input tweet?

The final graded relevance levels were determined using the following mapping scheme:

\[
\text{if } \text{Coherent AND Topically Relevant} \\
\quad \text{if Context-independent AND Non-repetitive} \\
\quad \quad \text{RelevanceLevel} = L2 \\
\quad \text{else} \\
\quad \quad \text{RelevanceLevel} = L1 \\
\text{else} \\
\quad \quad \text{RelevanceLevel} = L0.
\]

Following the quadratic gain value setting often used for web search evaluation (Burges et al., 2005) and for computing ERR (Chapelle et al., 2009), the Chinese subtask organisers mapped the L2, L1, and L0 relevance levels to the following gain values: \(2^2 - 1 = 3, 2^1 - 1 = 1, 2^0 - 1 = 0\); according to the present survey of NTCIR retrieval tasks, this is the only case where a quadratic gain value setting was used instead of the linear one. The evaluation measures used for this subtask were nG@1, P+, and normalised ERR (nERR). As for the Japanese subtask which used Japanese Twitter data, the same mapping scheme was applied, but the scores \(((L2, L1, L0) = (2, 1, 0))\) from 10 assessors were averaged to determine the final gain values; a binary-relevance, set-retrieval accuracy measure was used instead of P+, along with nG@1 and nERR.

The NTCIR-13 STC task (Shang et al., 2017) was similar to its predecessor, although systems were allowed to generate responses instead of retrieving existing tweets. The Chinese subtask used the following new criteria and the mapping scheme to obtain per-assessor graded relevance scores:

Fluent The response is acceptable as a natural language text;
Coherent The response is logically connected and topically relevant to the input post;
Self-sufficient The assessor can judge that the response is appropriate by reading just the post-response pair;
Substantial The response provides new information in the eye of the author of the input post.

\[
\text{if } \text{Fluent AND Coherent} \\
\quad \text{if Self-sufficient AND Substantial} \\
\quad \quad \text{AssessorScore} = 2 \\
\quad \text{else} \\
\text{else}
\]
AssessorScore = 1
else
    AssessorScore = 0.

Finally, 7-point relevance levels L0 through L6 were obtained by summing up the assessor scores, and a linear gain value setting was used to compute nG@1, P+, and nERR. In addition, an alternative approach to consolidating the assessor scores was explored, by considering the fact that some receive unanimous ratings while others do not even if they are the same in terms of the sum of assessor scores. More specifically, the raw gain value $g_{v}$ (i.e., sum of the assessor scores) was “upgraded” based on unanimity as follows (Sakai, 2017):

$$ugv = gv + pN(D_{max} - D),$$

(13)

where $p$ is an upgrade strength parameter (set to $p = 0.2$), $N$ is the number of assessors ($N = 3$ for the subtask), $D_{max}$ is the highest possible assessor score ($D_{max} = 2$ in this case), and $D$ is the difference between the highest and the lowest assessor scores for the item in question. For example, while a response labelled $(2, 1, 1)$ and another labelled $(2, 2, 0)$ would receive the same raw gain value of 4, the unanimity-aware gain values would be 4.6 and 4.0, respectively.

The NTCIR-13 STC Japanese subtask used Yahoo! News Comments data (user interactions on an online news article page) instead of Japanese Twitter data. Accordingly, the following new criteria for obtaining per-assessor scores were used:

Fluent  The response is fluent and understandable from a grammatical point of view (possible scores: 1,0);
Coherent  The response maintains coherence with the news topic and the input comment (possible scores: 1,0);
Context-dependent  The response depends on and is related to the input comment (possible scores: 2,1,0);
Informative  The response is informative and influences the author of the comment (possible scores: 2,1,0).

Note that the Context-dependence and Informativeness criteria are not binary. The Japanese subtask used the following two different schemes to map the scores to per-assessor scores:

SCHEME1:
if Fluent AND Coherent
    if Context-dependent == 2 AND Informative == 2
        AssessorScore = 2
    else
        AssessorScore = 1
else
    AssessorScore = 0.

This criterion is different from Context-independence used in the NTCIR-12 STC task.
SCHEME2:
if Fluent AND Coherent
  if Context-dependent == 2 AND Informative == 2
    AssessorScore = 2
  else if Context-dependent == 0 OR Informative == 0
    AssessorScore = 0
  else
    AssessorScore = 1
else
  AssessorScore = 0.

Five assessors independently judged each response and the per-assessor scores were averaged to compute the evaluation measures: nG@1, nERR, and the binary accuracy.

Although the Chinese Emotional Conversation Generation (CECG) subtask of the NTCIR-14 STC subtask (Zhang and Huang, 2019) is not exactly a ranked retrieval task, we discuss it here as it is a successor of the previous Chinese STC subtasks and utilises graded relevance measures. Given an input tweet and an emotional category such as Happiness and Sadness, participating systems for this subtask were required to return one generated response. In addition to the aforementioned Fluency and Coherence criteria, assessors were asked to judge whether the returned response is consistent with the emotional category specified in the input. The following mapping scheme was used to determine per-assessor relevance levels:

if Fluent AND Coherent
  if Emotion-Consistent
    RelevanceLevel = L2
  else
    RelevanceLevel = L1
else
  RelevanceLevel = L0.

The above relevance levels from three crowd workers were consolidated on a majority-vote basis, but if all three labels differed from one other (i.e., L2 vs. L1 vs. L0), the final relevance level was set to L0. As for the evaluation measures, the relevance scores \((L2, L1, L0) = (2, 1, 0)\) of the returned responses were simply summed or averaged across the test topics.

4.10 WWW (NTCIR-13 and -14) and CENTRE (NTCIR-14)

The NTCIR-13 We Want Web (WWW) Task (Luo et al., 2017) was an adhoc web search task. For the Chinese subtask, three assessors independently judged each
pooled web page on a 4-point scale: highly relevant (3 points), relevant (2 points), marginally relevant (1 point), and nonrelevant (0 points); the scores were then summed up to form the final 10-point relevance levels, L0 through L9. For the English subtask, two assessors independently judged each pooled web page on a different 4-point scale: highly relevant (2 points), relevant (1 point), nonrelevant (0 points), and error (the web page from clueweb12-B13 could not be displayed properly on the judgement interface; also 0 points); the scores were then summed up to form the final 5-point relevance levels, L0 through L4. In both subtasks, linear gain value settings were used to compute (Microsoft) nDCG, Q (the cutoff-based version given by Eq. 3), and nERR.

The NTCIR-14 WWW Task [Mao et al, 2019] was similar to its predecessor. The Chinese subtask used the following judgment criteria: highly relevant (3 points), relevant (2 points), marginally relevant (1 point), nonrelevant (0 points), garbled (similar to “error” mentioned above; also 0 points). Although three assessors judged each topic, the final relevance levels were obtained on a majority-vote basis rather than taking the sum; hence 4-point scale relevance levels L0 through L3 were used this time. As for the English subtask, 5-point relevance levels were obtained by following the methodology of the NTCIR-13 English subtask. Both subtasks adhered to Microsoft nDCG, (cutoff-based) Q, and nERR with linear gain value settings.

The NTCIR-14 CLEF NTCIR TREC Reproducibility (CENTRE) task [Sakai et al, 2019] encouraged participants to replicate a pair of runs from the NTCIR-13 WWW English subtask and to reproduce a pair of runs from the TREC 2013 Web Track adhoc task [Collins-Thompson et al, 2014]. Additional relevance assessments were conducted on top of the official NTCIR-13 WWW English test collection, by following the relevance assessment methodology of the WWW subtask. As for the evaluation of the TREC runs with the TREC 2013 Web Track adhoc test collection, the original 6-point scale relevance levels Navigational, Key, Highly relevant, Relevant, Nonrelevant, Junk were mapped to L4, L3, L2, L1, L0, L0 respectively. All runs involved in the CENTRE task were evaluated using Microsoft nDCG, (cutoff-based) Q, and nERR, with linear gain value settings.

### 4.11 AKG (NTCIR-13)

The NTCIR-13 Actionable Knowledge Graph (AKG) task [Blanco et al, 2017] had two subtasks: Action Mining (AM) and Actionable Knowledge Graph Generation (AKGG). Both of them involved graded relevance assessments and graded relevance measures. The AM subtask required systems to rank actions for a given entity type and an entity instance: for example, given “Product” and “Final Fantasy VIII,” the ranked actions could contain “play on Android,” “buy new weapons” etc. Two sets of relevance assessments were collected by means of crowdsourcing: the first set judged the verb parts of the actions (“play”, “buy” etc.) whereas the second

31 [http://lemurproject.org/clueweb12/](http://lemurproject.org/clueweb12/)
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set judged the entire actions (verb plus modifier as exemplified above). Both sets of judgements were done based on 4-point relevance levels: L0 through L3. The AKGG subtask required participants to rank entity properties: for example, given a quadruple (Query, Entity, Entity Types, Action)=("request funding," “funding,” “thing, action,” “request funding”), systems might return “Agent,” “ServiceType,” “Result” etc. Relevance assessments were conducted by crowd workers on a 5-point scale: L4 (Perfect), L3 (Excellent), L2 (Good), L1 (Fair), and L0 (Bad). Both sub-tasks used nDCG and nERR for the evaluation. Again, linear gain value settings were used.

4.12 OpenLiveQ (NTCIR-13 and -14)

The NTCIR-13 OpenLiveQ task [Kato et al, 2017] required participants to rank Yahoo! Chiebukuro questions for a given query, and the offline evaluation part of this task involved ranked list evaluation with graded relevance. Five crowd workers independently judged a list of questions for query q under the following instructions: “Suppose you input q and received a set of questions as shown below. Please select all the questions that you would want to click.” Thus, while the judgement is binary for each assessor, 6-point relevance levels (L0 through L5) were obtained based on the number of votes. (Microsoft) nDCG, Q, and ERR were computed using a linear gain value setting.

The NTCIR-14 OpenLiveQ-2 task [Kato et al, 2019] is similar to its predecessor, but this time the evaluation involved unjudged documents, as the relevance assessments from NTCIR-13 were reused but the target questions to be ranked were not identical to the NTCIR-13 version. The organisers therefore used condensed-list (Sakai, 2007a; Sakai and Kando, 2008) versions of Q, (Microsoft) nDCG, and ERR: that is, the measures are computed after removing all unjudged questions from the ranked lists. Also, for OpenLiveQ-2, the organisers switched their primary measure from nDCG to Q, as Q substantially outperformed nDCG (at \( l = 5, 10, 20 \)) in terms of correlation with online (i.e., click-based) evaluation in their experiments (Kato et al, 2018).

5 Summary

Table 1 summarises the ranked retrieval tasks of NTCIR discussed in Section 3, i.e., those that used binary relevance evaluation measures even though they collected graded relevance assessments. Similarly, Table 2 summarises the tasks discussed in Section 4 which fully utilised their graded relevance assessments by means of graded relevance measures. It can be observed that:

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32 Kindly confirmed by task organiser Hideo Joho in a private email communication (March 2019).
Table 1 NTCIR Ranked Retrieval Tasks with graded relevance assessments and binary relevance measures. Note that the relevance levels for the Patent Retrieval tasks of NTCIR-4 to -6 exclude the “nonrelevant” level: the actual labels are shown here because they are not simply different degrees of relevance (See Section 3.2).

| Task or Subtask          | NTCIR round (year) | Relevance levels | Main evaluation measures discussed in overview |
|--------------------------|--------------------|------------------|-----------------------------------------------|
| Japanese and JEIR        | 1 (1999)           | 3                | AP, R-precision, Precision, RP curves         |
| JEIR                     | 2 (2001)           | 4                | AP, R-precision, Precision, Interpolated Precision, RP curves |
| Chinese and CEIR         | 2 (2001)           | 4 per assessor   | RP curves                                     |
| CLIR                     | 3-5 (2002-2005)    | 4                | AP, RP curves                                 |
| Patent Retrieval         | 3 (2002)           | 4                | RP curves                                     |
| Patent Retrieval         | 4 (2004)           | A,B              | AP, RP curves                                 |
| Patent Retrieval         | 5 (2005)           | A,B              | CRS (for passage retrieval), AP               |
| Patent Retrieval         | 6 (2007)           | A,B / H,A,B (Japanese) | AP |
| Patent Retrieval         |                     | A,B (English)    | AP                                           |
| Spoken Document/Content  | 9-11 (2011-2014)   | 3                | AP and passage-level variants                 |
| SQ-SCR (SGS)             | 12 (2016)          | 3                | AP                                           |
| Math Retrieval           | 10 (2013)          | 5 mapped to 3    | AP, Precision                                 |
| Math Retrieval           | 11 (2014)          | 3                | AP, Precision, Bpref                         |
| MathIR                   | 12 (2016)          | 3                | Precision                                    |

- The majority of the past NTCIR ranked retrieval tasks, though not all of them, utilised graded relevance measures;
- Even a few relatively recent tasks, namely, SpokenQueryDoc and MathIR from NTCIR-12 held in 2016, refrained from using graded relevance measures.

As was discussed in Section 3.1, researchers should be aware that binary-relevance measures with different relevance thresholds (e.g. Relaxed AP and Rigid AP) cannot serve as substitutes for good graded-relevance measures. If the optimal ranked output for a task is defined as one that sorts all relevant documents in decreasing order of relevance levels, then by definition, graded relevance measures should be used to evaluate and optimise the retrieval systems.

One additional remark regarding Tables 1 and 2 is that the NTCIR-5 CLIR overview paper [Kishida et al, 2007] was the last to report on RP curves; the RP curves completely disappeared from the NTCIR overviews after that. This may be because (a) interpolated precisions at different recall points [Sakai 2014] do not directly reflect user experience; and (b) graded-relevance measures have become more popular than before.

What lies beyond graded relevance? Here is my personal view concerning offline evaluation (as opposed to online evaluation using click data etc.). Information Retrieval (IR) and Information Access (IA) tasks have diversified, and relevance assessments require more subjective and diverse views than before. We are no longer just talking about whether a scientific article is relevant to the researcher’s question.
Table 2  NTCIR Ranked Retrieval Tasks with graded relevance assessments and graded relevance measures. Binary-relevance measures are shown in parentheses.

| Task or Subtask | NTCIR round (year) | Relevance levels | Main evaluation measures discussed in overview |
|-----------------|---------------------|------------------|-----------------------------------------------|
| Web Retrieval   | 3 (2003)            | 4 + best documents | DCG ((W)RR, AP, RP curves)                     |
| WEB Informational| 4 (2004)            | 4                | DCG ((W)RR, Precision, RP curves)              |
| WEB Navigational| 3                   |                  | DCG, ((W)RR, UCS)                             |
| WEB Navigational| 5 (2005)            | 3                | DCG, ((W)RR)                                  |
| CLIR            | 6 (2007)            | 4                | nDCG, Q, generalised AP (AP)                   |
| IR4QA           | 7-8 (2008-2010)     | 3                | nDCG, Q (AP)                                  |
| GeoTime         | 8-9 (2010-2011)     | 3*               | GA-{nG@1, nDCG, Q}, (GA-Hit@1, BA-Hit@1) etc. |
| INTENT DR       | 9 (2011)            | 5                | D²-nDCG                                       |
| INTENT DR       | 10 (2013)           | 5                | D²-nDCG, DIN-nDCG, P+Q                       |
| IMine DR        | 11 (2014)           | 4 incl. Spam     | D²-nDCG                                       |
| IMine TaskMine  | 11                   | 6                | nDCG                                          |
| IMine QU        | 12 (2016)           | 3 (vertical)     | QU-score                                      |
| IMine VI        | 12                   | 3 (vertical)     | D²-nDCG, nDCG                                |
|                 |                      |                  | 3 (intentwise)                                |
|                 |                      |                  | 3 + Spam (topicwise)                          |
| RecipeSearch    | 11 (2014)           | 3(2)             | nDCG (AP, RR)                                 |
| Temporalia TIR  | 11                   | 3                | nDCG, Q, (Precision)                          |
| Temporalia TDR  | 12 (2016)           | 3                | nDCG, α-nDCG, D²-nDCG                         |
| STC Chinese     | 12 (2016)           | 3                | nG@1, P+, nERR                                |
| STC Chinese     | 13 (2017)           | 7(10)            | nG@1, P+, nERR                                |
| STC Japanese    | 12-13 (2017-2019)   | 3 per assessor   | nG@1, nERR (Accuracy)                        |
| STC CECG        | 14 (2019)           | 3                | sum/average of relevance scores               |
| WWW English     | 13-14 (2017-2019)   | 5                | nDCG, Q, nERR                                |
| WWW Chinese     | 13 (2017)           | 10               | nDCG, Q, nERR                                |
| WWW Chinese     | 14                   | 4                | nDCG, Q, nERR                                |
| AKG             | 13 (2017)           | 4 (AM) / 5 (AKGG) | nDCG, nERR                                   |
| OpenLiveQ       | 13-14 (2017-2019)   | 6                | nDCG, Q, ERR (with condensed lists at NTCIR-14) |
| CENTRE          | 14 (2019)           | 5                | nDCG, Q,nERR                                 |

*two types of partially relevant (when and where) counted as one level.

(as in Cranfield); we are also talking about whether a response of a chatbot is “relevant” response to the user’s utterance, about whether a reply to a post on social media is “relevant,” and so on. Graded relevance implies that there should be a single label for each item to be retrieved (e.g., “this document is highly relevant”), but these new tasks may require a distribution of labels reflecting different users’ points of view. Hence, instead of collapsing this distribution to form a single label, methods to preserve the distribution of labels in the test collection may become useful. The Dialogue Quality (DQ) and Nugget Detection (ND) subtasks of the NTCIR-14 STC task are the very first of NTCIR efforts in that direction; see also Higashinaka et al (2017), Maddalena et al (2017), and Sakai (2018).
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