

## Overview of CLIR Task at the Fourth NTCIR Workshop

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### Abstract

*This paper reviews research efforts in the NTCIR-4 CLIR task, which is a project involving large-scale retrieval experiments on cross-lingual information retrieval (CLIR) of Chinese, Japanese, Korean, and English. The project has four sub-tasks, multi-lingual IR (MLIR), bilingual IR (BLIR), pivot bilingual IR (PLIR) and single language IR (SLIR), in which many research groups from over ten countries are participating. This paper describes the system of the NTCIR-4 CLIR task and its test collection (document sets, topic sets, and method for relevance judgments),*

*and reviews CLIR techniques used by participants as well as the search performance of runs submitted for evaluation.*

**Keywords:** *Cross-lingual information retrieval; Evaluation, Retrieval experiment*

### 1 Introduction

Cross-lingual information retrieval (CLIR) is recognized as an important research theme in view of the global reach and growth of the Internet. In order to promote research on CLIR among three East-Asian (i.e., Chinese, Japanese and Korean) and English

languages, the CLIR task is again part of the NTCIR-4 project after the NTCIR-3 CLIR task [1] was completed in October 2002.

The NTCIR-4 CLIR task has taken over three subtasks from the previous task:

- *Multilingual CLIR* (MLIR),
- *Bilingual CLIR* (BLIR), and
- *Single Language IR* (SLIR),

and includes a new subtask, *Pivot Bilingual CLIR* (PLIR). PLIR is a special kind of BLIR in which a third language is employed as an intermediary for translating the source language into the target one, e.g., for Chinese-Japanese BLIR, Chinese query terms are translated into English words and then the set of English words is translated into Japanese words. The PLIR task will help solve problems of insufficient language resources for direct translation between East-Asian languages.

The document sets are extended for the NTCIR-4 CLIR task, i.e., 1998-99 Korean document records are added to the test collection (in the previous NTCIR-3, while Chinese (C), Japanese (J) and English (E) documents published in 1998 and 1999 are available, the publishing year of Korean (K) documents was 1994). The addition of documents allows us to conduct experiments on a CJKE multilingual collection. Also, the Japanese and English document sets are augmented in order to balance the size of the document sets in each language (in the NTCIR-3 collection, the English part is relatively small).

## 2 Design of the CLIR Task

### 2.1 Schedule

The Call for Participants (CFP) was first released in February 2003. The time schedule for the NTCIR-4 CLIR task is as follows.

- 2003-03-20: Deadline for applications
- 2003-03-30: Release of data (document sets)
- 2003-10-01: Distribution of search topics
- 2003-11-01: Submission of search results
- 2004-02-20: Delivery of evaluation results
- 2004-03-31: Deadline for papers (Working Notes)
- 2004-06: NTCIR Workshop 4 (Conference)

### 2.2 Subtasks

**2.2.1 Multilingual CLIR (MLIR).** In general, the document set of the MLIR subtask consists of two or more languages. For the NTCIR-4 CLIR task, the participants are allowed to submit the results of runs for two types of multilingual document collection:

- "*Large collection*": CJKE collection, which consists of Chinese (C), Japanese (J), Korean (K) and English (E) documents, and
- "*Small collection*": CJE collection, which consists of Chinese (C), Japanese (J), and English

(E) documents.

Regarding the topic set, participants can select one language from CJKE for each run. Therefore, there are eight combinations of topic sets and document sets, i.e.,

Topic set: C or J or K or E >>

Doc set: CJKE or CJE.

**2.2.2 Bilingual CLIR (BLIR).** BLIR means that the document set in a single language is searched for a topic in a different language, e.g., searching Japanese documents for Korean topics (K to J run). In the NTCIR-4 CLIR task, in principle participants are not allowed to submit the results of runs using topics written in English, except in the case of trying the pivot language approach (i.e., PLIR). The combinations of topics and documents for the BLIR subtask are as follows:

Topic set: C >>> Doc set: J or K or E

Topic set: J >>> Doc set: C or K or E

Topic set: K >>> Doc set: C or J or E

**2.2.3 Pivot Bilingual CLIR (PLIR).** This subtask is a new challenge in the NTCIR-4 CLIR task. As already mentioned, this approach employs a third language as an intermediary for translation of query or document texts. Also, the participants submitting runs for this subtask are allowed to also submit BLIR runs using English topics (i.e., E to C or J or K) in order to analyze the comparative performance of the approach. Thus, the combinations of topics and documents for the BLIR subtask are as follows:

Topic set: C >>> Doc set: J or K or E

Topic set: J >>> Doc set: C or K or E

Topic set: K >>> Doc set: C or J or E

Topic set: E >>> Doc set: C or J or K

(with no pivot)

**2.2.4 Single Language IR (SLIR).** The topic set and document sets of SLIR are written in the same language. The combinations of topics and documents for the SLIR subtask are as follows:

Topic set: C >>> Doc set: C

Topic set: J >>> Doc set: J

Topic set: K >>> Doc set: K

Topic set: E >>> Doc set: E

### 2.3 Topic fields and run types

**2.3.1 Types of runs.** Basically, each topic consists of four fields, i.e., "T" (TITLE), "D" (DESC), "N" (NARR) and "C" (CONC) (see below for details). We can categorize search runs based on the fields used for execution. In the NTCIR-4 CLIR task, the following types of runs are adopted:

- *Mandatory runs*: T-run and D-run

Each participant must submit two types of run for each combination of topic language and docu-

ment language(s):

*T-run*, for which only the TITLE field is used,

*D-run*, for which only the DESC field is used

The purpose of asking participants to submit these mandatory runs is to clarify the research findings by comparing systems or methods under consistent conditions.

- *Recommended runs*: DN-run

Participants are also recommended to execute the DN run, which employs both the <DESC> and <NARR> fields.

- *Optional runs*

Any other combinations of fields are allowed to be submitted as optional runs according to each participant's research interests, e.g., TDN-run, DC-run, TDNC-run and so on.

**2.3.2 Number of runs.** Each participant can submit up to five runs in total for each language pair regardless of the type of run, and participants are allowed to include up to two T-runs in maximum and also up to two D-runs within the five runs. "Language pair" means the combination of topic language and document language(s). For example,

Language combination - Topic: C and Docs: CJE (C to CJE)

Submission - two T-runs, a D-run, a DN-run and a TDNC run (5 runs in total).

**2.3.3 Identification and priority of runs.** Each run must be associated with a RunID, which is an identifier for each run. The format of the RunID is as follows.

Group's ID - Topic Language - Document Language - Run Type - pp

"pp" is two digits used to represent the priority of the run, and is used as a parameter for pooling. The participants must decide the priority for each submitted run among them for each language pair. "01" means the highest priority. For example, a participating group, LIPS, submits three runs for C to CJE. The first is a T-run, the second is a D-run and the third is a DN-run. Therefore, the RunID for each run is LIPS-C-CJE-T-01, LIPS-C-CJE-D-02, and LIPS-C-CJE-DN-03, respectively. Or, if the group uses different ranking techniques in T run for C to CJE, the RunID for each run must be LIPS-C-CJE-T-01, LIPS-C-CJE-T-02, and LIPS-C-CJE-D-03.

### 3 Test Collection

#### 3.1 Document Sets

The documents used for the NTCIR-4 CLIR task are news articles collected from various news agencies from different countries. Table 1 shows the sources and numbers of records in the document collections.

The tags used for separating each field in a record are also indicated in Table 2.

**Table 1 Document sets for the NTCIR-4 CLIR task**

Sources	No. of Docs	
<i>Chinese 1998-99</i>		
CIRB020 (United Daily News)	249,203	
CIRB011 (China Times, China Times Express, Commercial Times, China Daily News, Central and Daily News )	132,172	
Total	<b>381,375</b>	
<i>Japanese 1998-99</i>		
Mainichi	220,078	
Yomiuri	373,558	
Total	<b>593,636</b>	
<i>Korean 1998-99</i>		
Hankookilbo	149,921	
Chosunilbo	104,517	
Total	<b>254,438</b>	
<i>English 1998-99</i>		
EIRB010	Taiwan News	7,489
	China Times English News (Taiwan)	2,715
Mainichi Daily News (Japan)		12,723
Korea Times		19,599
Xinhua (AQUAINT)		208,167
Hong Kong Standard		96,683
Total	<b>347,376</b>	

**Table 2 Tags used for identifying each field**

<i>Mandatory tags</i>	
<DOC>	The tag for each document
<DOCNO>	Document identifier
<LANG>	Language code: CH, EN, JA, KR
<HEADLINE>	Title of this news article
<DATE>	Issue date
<TEXT>	Text of news article
<i>Optional tags</i>	
<P>	Paragraph marker
<SECTION>	Section identifier in original newspapers
<AE>	Whether contains figures or not
<WORDS>	Number of words in 2-bytes (for Mainichi Newspaper)

#### 3.2 Topic

Each topic has four fields: T (TITLE), D (DESC), N (NARR), and C (CONC). The following shows a sample topic.

<TOPIC>

<NUM>009</NUM>  
 <SLANG>CH</SLANG>  
 <TLANG>EN</TLANG>  
 <TITLE>Japan, South Korea, Fishery Agreement</TITLE>  
 <DESC>Find articles on the content of the final fishery agreement between Japan and South Korea</DESC>  
 <NARR>  
 <BACK>There are frequent disputes between Japan and South Korea because of the 35 years of colonized reign. Things worsened in January of 1998 when Japan announced the abolishment of the fishery agreement of 1965. Finally, in September of 1998, a new fishery agreement between Japan and South Korea was reached despite disputes over the sovereignty of the isles. It marked an end to eight months of serious disputes between the two countries. Please query the content of this new agreement for things such as allocation of fishing areas and results of negotiation.</BACK>  
 <REL>Documents of reports on the final fishery agreement are relevant. Reports on historical disputes and events between Japan and South Korea are not relevant.</REL>  
 </NARR>  
 <CONC>Japan, South Korea, Fishery Agreement, Isles, Fishing Area</CONC>  
 </TOPIC>

The tags used in topics are shown in Table 3. The topics were created in Taiwan, Japan and Korea separately (see also Table 4), and finally 60 topics were selected based on the results of feasibility tests checking the numbers of relevant documents in each document set. The original language used in the process of creating topics is recorded in the <SLANG> field.

Subsequently, the selected 60 topics were translated into English, and each English topic was translated into each Asian language except the original language. All translation was done by human translators. Through the process, four language (CJKE) versions of all 60 topics were prepared.

**Table 3 Topic tags used in the NTCIR-4 CLIR task**

<TOPIC>	The tag for each topic
<NUM>	Topic identifier
<SLANG>	Source language code: CH, EN, JA, KR
<TLANG>	Target language code: CH, EN, JA, KR
<TITLE>	The concise representation of information request, which is composed of noun or noun phrase
<DESC>	A short description of the topic. A brief description of the information

	need, which is composed of one or two sentences.
<NARR>	A much longer description of the topic. <NARR> may have three parts: (1) <BACK>...</BACK>: background information about the topic is described. (2) <REL>...</REL>: further interpretation of the request and proper nouns, the list of relevant or irrelevant items, the specific requirements or limitations of relevant documents, and so on are given. (3) <TERM>...</TERM>: definition or explanation of proper nouns, scientific terms and so on.
<CONC>	Keywords relevant to the whole topic.

**Table 4 Distribution of topics by source**

Source	Numbers	Topic ID
Taiwan	14	No. 001 - 014
Korea	21	No. 015 - 035
Japan	25	No. 036 - 060
Total	60	

**Table 5 Regional distribution of participants**

	No. of groups*	Submitted		
		SLIR	BLIR	MLIR
Australia	1 (1)		1	
Canada	1 (0)	1		
China	2 (2)	1	1	
(Hong Kong)	1 (1)	1		
Japan	9 (4)	7	6	2
Korea	2 (2)	1	2	
Singapore	1 (1)	1		
Switzerland	1 (1)	1		1
Taiwan	2 (2)	1	1	1
USA	6 (4)	5	6	1
Total	26 (17)	19	17	5

\* ( ) indicates the number of universities and other research institutes.

## 4 Submission of Results

In total, search results were submitted by 26 groups from ten countries and regions (see Table 5). Regarding the numbers of participants, Japan is dominant (9 groups), followed by the USA (6 groups), China and Hong Kong (3 groups), and Taiwan (2 groups). Appendix 1 shows the names of groups submitting the results.

Unfortunately, seven groups that applied to participate in the NTCIR-4 CLIR task did not submit final results for some reasons.

Table 6 shows the numbers of submitted runs and of groups. In total, 368 runs were submitted, of which 182 (49.5%) were for SLIR, 149 (40.5%) were for BLIR (including PLIR), and 37 (10.1%) were for MLIR.

**Table 6 Statistics on submissions for the NTCIR-4 CLIR task**

Sub-tasks	Run types	No. of runs	No. of groups
SLIR	C-C	52	13
	J-J	58	14
	K-K	31	8
	E-E	41	10
	Total	182	19*
BLIR (and PLIR)	J-C	8	2
	K-C	5	1
	E-C	12	3
	C-J	18	5
	K-J	13	4
	E-J	15	4
	C-K	8	2
	J-K	8	2
	E-K	7	2
	C-E	24	7
	J-E	23	6
	K-E	8	2
	Total	149	17*
	MLIR	C-CJE	9
J-CJE		5	1
E-CJE		15	3
J-CJKE		3	1
E-CJKE		5	1
Total		37	5*
Total		368	26

\*It should be noted that a group can submit more than one result within each sub-task.

## 5 Results of Relevance Judgments

### 5.1 Procedure of relevance judgments

Evaluation in the NTCIR-4 CLIR task is based on a TREC-like procedure using the results of relevance judgments of each pool of retrieved documents for topics (Table 7 shows the size of each pool for identifying relevant documents). The trec\_eval program was used to score search results submitted by participants.

For keeping measurement granularity, each document is assigned one of four degrees of relevance in the judgment process: S (highly relevant), A (relevant), B (partially relevant), or C (irrelevant). In the CLIR task, we define

- *Rigid relevant*: S+A
- *Relaxed relevant*: S+A+B

because the trec\_eval scoring program adopts binary relevance. Therefore, two kinds of relevance judgment files (rigid and relaxed) for each collection (C, J, K, E, CJE, and CJKE) are prepared by the task organizers.

**Table 7 Pool size and the numbers of documents judged by each language**

Topic	Pool size	No. of documents judged			
		C	J	K	E
001	100	1657	3435	1275	2194
002	100	1455	2631	1662	2327
003	100	1145	1257	909	1220
004	100	2102	3257	1234	1818
005	100	1934	2185	481	1662
006	100	1194	1825	599	1327
007	100	1286	653	990	661
008	100	1493	1950	906	1890
009	100	1635	1110	664	1139
010	100	1380	1235	1136	2444
011	100	1029	1480	1474	1655
012	100	1939	2352	1721	2530
013	100	1438	2880	973	2553
014	100	1148	1508	614	1953
015	100	1309	1169	1291	1845
016	100	1082	1430	748	1164
017	100	1191	1544	723	1414
018	80	2116	3560	2054	2349
019	80	2650	3633	1771	2970
020	100	1742	2719	1338	2513
021	100	960	1178	797	1320
022	100	2637	3000	971	2468
023	100	1951	2251	987	1568
024	100	1486	2412	925	2182
025	100	2102	2073	1275	2918
026	100	2392	1192	1120	2198
027	100	1788	1898	1253	2509
028	100	1399	2025	982	2096
029	100	1993	1426	763	1600
030	100	1452	1337	558	1261
031	100	1038	2168	575	2442
032	100	2362	2115	924	3359
033	100	1488	2523	954	1583
034	100	1359	2627	1278	2429
035	100	2363	2750	1313	2695
036	100	1368	1327	728	1476
037	100	1735	2547	1854	2122
038	80	2228	3092	1829	3519
039	80	2168	2532	1634	3131
040	100	1542	2296	1530	1972

041	100	1764	1581	1429	1847
042	100	1619	1119	1293	1465
043	100	2069	1847	1103	3094
044	100	640	1381	516	1710
045	100	1612	1861	1437	1302
046	100	1149	1193	664	1101
047	100	1076	1524	515	2005
048	100	1288	1318	659	2040
049	100	1415	1892	746	2153
050	100	1172	1622	1015	2031
051	100	1091	1259	668	1365
052	100	2202	1998	2011	1772
053	100	1788	1073	1227	1887
054	100	1072	1568	495	1693
055	100	774	1923	1483	1715
056	100	1655	2545	1031	1610
057	80	2376	2632	1792	3039
058	100	1444	2344	1390	2405
059	100	1384	1698	836	1883
060	100	2079	2716	1305	2163

## 5.2 Relevant documents and effective sets of topics for evaluation

Appendix 2 indicates the numbers of relevant documents included in the document sets. As Appendix 2 shows, there are some topics for which there are very few relevant documents. Therefore, the task organizers decided to employ again the so-called “3-in-S+A” criterion, which was applied at NTCIR-3. This criterion means that only those topics having three or more “rigid” relevant documents are used for evaluation.

According to this criterion, the sets of topics for each document collection are as follows:

### 1. Topics for SLIR BLIR and PLIR

- (1) Chinese Collection (C): 59 topics (ID: 001-024, 026-060) are used for evaluation. Topic 025 is removed.
- (2) Japanese Collection (J): 55 topics (ID: 003-021, 023-024, 026-037, 039-060) are used for evaluation. Topics 001, 002, 022, 025 and 038 are removed.
- (3) Korean Collection (K): 57 topics (ID: 002-009, 012-060) are used for evaluation. Topics 001, 010 and 011 are removed.
- (4) English Collection (E): 58 topics (ID: 002-037, 039-060) are used for evaluation. Topics 001 and 038 are removed.

### 2. Topics for MLIR

CJE and CJKE: All 60 topics are used (no topic is

removed).

## 5.3 Topics with over 1000 relevant documents

The NTCIR-4 document collection is bigger than that of the NTCIR-3. Thus, a few topics have over 1000 relevant documents (see Table 9) as follows.

### 1. Topics for SLIR, BLIR and PLIR

(1) English Collection (E): The number of relaxed relevant (S+A+B) documents to topic 044 is over 1000.

### 2. Topics for MLIR

(2-1) CJE: The number of relaxed relevant (S+A+B) documents to topic 057 is over 1000.

(2-2) CJKE: The number of rigid relevant (S+A) documents to topic 044 is over 1000, and the number of relaxed relevant (S+A+B) documents to topics 044, 045, 047, 054, 055, and 057 is over 1000.

If the number of relevant documents is over 1000, the upper limit of average precision computed by the trec\_eval scoring program is less than 1.0. For example, when the number of relevant documents is 1072, the upper limit seems to be  $1000/1072 (= 0.9328)$ .

## 6 Overview of CLIR Methods

### 6.1 Indexing methods

**6.1.1 Indexing of CJK text.** As is widely known, it is important for IR on East-Asian languages (i.e., Chinese, Japanese and Korean) to segment each sentence or each phrase with no word boundary, and then to identify useful index terms (Korean text includes white spaces as delimiters between phrasal units). In the NTCIR-4 CLIR task, the following methods are used:

- Morphological analysis (or POS tagging)
- Matching with a machine readable dictionary
- Overlapping bigram
- Character-based indexing (for Chinese text)

For word-based indexing of Chinese text, the IFLAB group [2] seems to use a Chinese morphological tool, SuperMorph<sup>1</sup>. The UCNTC group [3] employs the NMSU segmenter *ch\_seg* to identify Chinese words.

Also, many groups seem to be developing their own algorithms for segmenting Chinese text as follows.

- FJUIR group [4]: an algorithm by Tseng [5]
- I2R group [6]: a *seeding-and-expansion* mechanism
- OKI group [7]: a statistical Chinese word segmenter

<sup>1</sup> <http://www.omronsoft.com/>

- JSCCC group [8]: a statistical part-of-speech tagger for tokenization and finite state grammar (the JSCCC group also has such tools for Japanese and English text)
- ISCAS group [9]: a *bi-directional maximal match algorithm*
- KLE group [10]: a morphological tokenizer (they also developed tokenizers for Chinese and Japanese)
- AILAB groups [11]: phrase identification based on mutual information using co-occurrence statistics

In the case of Japanese text, most of the groups seem to make use of ChaSen<sup>2</sup>. Meanwhile, in order to extract index terms from Korean text, the following morphological analyzers or tokenizers are used in the NTCIR-4 CLIR task:

- HAM5.0<sup>3</sup> (used by CRL group [12] and PIRCS group [13])
- LinguistX toolkit<sup>4</sup> (tlrrd group [14])
- Kemorphor<sup>5</sup>(IFLAB group [2])
- a Korean part-of-speech tagger (KUNLP group [15], see also Kim et al.[16])

In order to investigate the effectiveness of such indexing techniques, some groups have tried to compare the performance between indexing methods as follows.

- PolyU group [17]: character-based indexing, bi-gram indexing and hybrid indexing for Chinese(C)
- HUM group [18]: word-based indexing and overlapping n-grams for CJK

**6.1.2 Removing stopwords.** The RCUNA group [19] employs again a stopwords dictionary used in the NTCIR-3 CLIR task. The BRKLY group [20] also uses a Japanese stopwords list developed in the NTCIR-3. In the case of the bi-gram approach, the UniNE group [21] removes the most frequent bi-grams (CJK).

Some groups use a stopwords list for removing general words in queries such as “describe” or “document” (for example, see the JSCCC group’s paper [8]). In particular, the tlrrd group [14] is investigating intensively two approaches for developing such stopwords lists, using (1) collection statistics and (2) query log statistics.

**6.1.3 Decomposing.** The HUM group [18] reported the effects of decomposing CJK multi-words terms. In order to break Japanese compound words into components, the CRL group [12] proposes the *all term-pattern method*, in which all overlapped combinations of components included in

a compound word are used as index terms. Regarding Korean compound words, the tlrrd group [14] tries to decompose them based on their own method developed for decomposing German words.

## 6.2 Translations

### 6.2.1 Query translation vs. document translation.

In the NTCIR-4 CLIR task, most of the groups adopt the query translation approach. Meanwhile, the KLE group [10] is investigating a combination of query translation and *pseudo-document translation* (PDT) which simply replaces terms included in each document into corresponding translations using bilingual dictionaries. A similar approach is being taken by the BRKLY group [20], called *fast document translation*.

**6.2.2 Translation methods and resources.** For translating queries or documents, the following language resources are employed in the NTCIR-4 CLIR task.

- Machine translation (MT) systems
- Bilingual dictionaries
- Parallel corpora

Various bilingual resources are used for query translation by research groups participating in the NTCIR-4 CLIR task as follows.

- [C-E]
- Systran MT software (<http://systransoft.com/>)
- Loto MT software (<http://lotousa.com/>)
- LDC Chinese-English dictionary (<http://www ldc.upenn.edu/>)
- CEDICT (<http://www.mandarintools.com/cedict.html>)
- BDC Chinese-English dictionary (<http://www.bdc.com.tw/>)
- MDBG Chinese-English dictionary (<http://www.mdbg.net/chindict/chindict.php>)
- CETA (distributed by MRM Corp.)
- EvDict
- Babylon (bilingual dictionary)

- [C-J]
- MT system currently being developed at Toshiba
- Hourai for Windows (MT software) (<http://www.corsslanguag.co.jp/english/>)
- Dr. eye dictionary (<http://www.dreye.com/>)

- [J-K]
- Kourai for Windows (MT software) (<http://www.corsslanguag.co.jp/english/>)
- Dictionaries by UNISOFT Corp.

- [J-E]
- Babelfish (MT system) (<http://babelfish.altavista.com/>)
- YakushiteNet (MT system) (<http://www.yakushite.net/>)

<sup>2</sup> <http://chasen.aist-nara.ac.jp/>

<sup>3</sup> <http://nlp.kookmin.ac.kr/HAM/kor/download.html>

<sup>4</sup> <http://www.inxight.com/products/oem/liguistx>

<sup>5</sup> <http://www.crosslanguage.co.jp/english/>

- Toshiba MT system
- PC-Transer (MT Software)  
(<http://www.corsslanguange.co.jp/english/>)
- L&H J-Surf (translation tool for Web pages)
- EDR bilingual dictionary  
(<http://www.ijnet.or.jp/edr/E05JEBIL.txt>)
- EDICT  
(<http://www.csse.monash.ed.au/~jwb/edict.html>)
- Atok (commercial dictionary)  
(<http://www.atok.com/>)
- Babylon (bilingual dictionary)
- Japanese-English News Article Alignment Data  
(<http://www2.crl.go.jp/jt/a132/member/mutiyama/jea>)

[K-E]

- Babelfish (MT system)  
(<http://babelfish.altavista.com/>)
- Systran MT software  
(<http://systransoft.com/>)
- EnGuide MT software  
(<http://www.lnisoft.co.kr/>)
- Babylon (bilingual dictionary)

The UniNE group [21] is investigating the relative effectiveness of various bilingual resources on search performance. As a translation method, the OKI group [7] is using cross-lingual PRF (CLPRF) method [22] for translating query terms, in which pseudo-relevance feedback (PRF) is executed on a parallel corpus or a bilingual dictionary to extract translation candidates.

**6.2.3. Multi-word term translation.** The JSCCC group [8] is attempting to translate multi-word terms based on their previous work, in which term frequency statistics in a reference corpus are used.

**6.2.4 Estimation of translation probabilities.** When a language model (see below) for CLIR is applied, translation probabilities have to be estimated. The FORES group [23] is using their own method for computing translation probabilities (E to J) from a parallel corpus based on the probabilistic latent indexing method (PLSA).

**6.2.5 Translation disambiguation.** In the IR field, various techniques for translation disambiguation have been proposed. In the NTCIR-4 CLIR task, the following methods are employed:

- Using a parallel corpus (JSCCC group [8])
- Using co-occurrence statistics in the target documents collection (KUNLP group [15] and RMIT group [24])
- Using the number of Web pages including a pair of translation candidates (AILAB group [11]).
- Using a probabilistic method based on a language model (IFLAB group [2])
- Using a Web directory (UENIS group [25])

- Pre-translation expansion (see section 6.5)

In the KUNLP group's study, translations are selected according to scores computed based on a mutual information (MI) measure. The RMIT group [24] proposes a probabilistic disambiguation method based on the hidden Markov model (HMM). The UENIS group [25] is investigating a novel method, in which information for disambiguation is extracted from Web documents within a Web category matching the query.

Furthermore, the UCNTC group [3] applies a structured query method using the "#syn" operator of INQUERY for coping with the translation disambiguation problem.

**6.2.6 Out-of-vocabulary problem.** In general, MT systems or bilingual dictionaries cannot cover all words included in queries, and unknown words are often detected in the process of translation. To solve the out-of-vocabulary problem, the KUNLP group [15] tries to expand bilingual dictionaries using Web resources. They collected translation information of unknown words from the Web manually.

Web resources are also used by the PIRCS group [13] to extract automatically translations of unknown words. A similar approach was adopted in the RMIT group's study [24], in which a sophisticated Web mining algorithm for identifying translations of unknown Chinese words was developed. They use the Google search engine and procedure for extracting English equivalents from Chinese Web documents based on co-occurrence statistics.

**6.2.7 Transliteration.** Another useful method for solving the out-of-vocabulary problem is transliteration. The KUNLP group [15] tries to transliterate unknown Korean words into English word candidates based on phonetic information for K to E runs. Meanwhile, the IFLAB group [2] uses transliteration dictionaries for Japanese *Katakana* words and Korean words, which were automatically created based on a probabilistic model. Also, the KLE group [10] attempts to transliterate Chinese characters into *Hangul* for translating Chinese or Japanese text into Korean.

**6.2.8 Combination of MT systems.** The PIRCS group [13] and UniNE group [21] attempted to merge translation results from two MT systems for enhancing BLIR performance.

**6.2.9 Cognate matching.** In the case of C to J bilingual IR, the BRKLY group [20] is investigating the effectiveness of a non-translation strategy, which just converts Chinese characters (BIG5) to Japanese characters (EUC-J) with no translation. This approach can be considered as a kind of cognate matching technique.



### 6.3 Pivot language approach

One of the important research issues in the NTCIR-4 CLIR task is the pivot language approach, which has the potential for coping with lack of direct bilingual resources between languages. In total, five research groups are challenging this issue as follows:

- The PIRCS group [13] uses English as a pivot for executing C to K runs
- The OKI group [7] uses English as a pivot for executing C to J and J to C runs.
- The tlrrd group [14] uses English as a pivot for executing C to J and K to J runs.
- The TSB group [26] uses Japanese language as a pivot for C to E retrieval.

### 6.4 Retrieval models

**6.4.1 Models.** Most of the research groups participating in the NTCIR-4 CLIR task use standard retrieval models such as Okapi BM11 and BM25, vector space model (VSM), logistic regression model, INQUERY, PIRCS, language model (LM) and so on.

The Okapi formula is begin modified by some groups. For example, the CRL group [12] extends the Okapi BM25 formula to incorporate information on term location, type of term (proper noun and numerical term) and so on. They also add the number of queries including the term into their formula so that the weight of a general term in queries decreases. The JCSSS group [8] puts a coefficient into the BM25 formula in order to apply *Fujita's method* [27], which decreases the weight of phrasal terms. *Fujita's method* is also used by the CRL group [12] in the process of extracting terms from Japanese text.

Some research groups are trying to apply LM to SLIR or CLIR issues as follows.

- The PLLS group [28] examines KL-divergence of probabilistic language models with Dirichlet prior smoothing.
- The FORES group [23] uses LM for CLIR proposed by Xu et al. [29], in which translation probabilities are directly incorporated into the model.
- The ISCAS group [9] compares effectiveness between LM and Okapi BM25, and also proposes the *trigger LM*, in which dependency between index terms is incorporated.

The UniNE group [21] applies the Prosit approach, a kind of probabilistic model.

**6.4.2 Comparison of performance.** The FJUIR group [4] compares the performance between Okapi BM11 and a variation of VSM for C to C monolingual runs. The UniNE group [21] compares the performance between various retrieval models such as Prosit, VSM and Okapi.

**6.4.3 Data fusion.** The UniNE group [21] is extensively investigating data fusion strategies that merge the search results from different retrieval models. They compare performance between five strategies, round-robin, simple linear combination of individual scores, normalized score, Z-score and a variation of Z-score. KLE group [10] also examines effectiveness of merging some ranked lists for SLIR of CJKE. The ranked lists were generated by selecting a combinatory pattern of indexing methods (bi-grams or word-based) and search algorithms (Okapi or LM). PLLS group [28] tries to score documents in a TD-run by mixing individual scores from a T-run and a D-run.

### 6.5 Query expansion

**6.5.1 Standard PRF.** As widely known, pseudo-relevance feedback (PRF) or blind feedback brings us improvement of retrieval performance. Therefore, it seems that most of research groups participating in the NTCIR-4 CLIR task apply standard PRF techniques, i.e., Rocchio method or Robertson's probabilistic method.

In particular, the TSB group [26] proposes two new *Flexible PRF* methods, *Term Exhaustion* and *Selective Sampling*, and examines experimentally their effectiveness. The JSCCC group [8] tries to compare the performance between two PRF methods, Rocchio and "Prob2," where "Prob2" is a variation of probabilistic feedback method. The PolyU group [17] and BRKLY group [20] attempt analyzing effects of parameters in PRF (the number and weight of selected terms and the number of top documents) on retrieval performance. The PolyU group [17] also proposes "title re-ranking method," in which documents are re-ranked according to a matching score between titles of the query and of the document.

Some research groups challenge to use non-standard PRF methods. For example, the OKI group [7] and KLE group [10] adopt Ponte's ratio method. The RMIT group [24] proposes a new-type PRF method, in which statistics on word co-occurrence of a given word and a query terms in top-ranked documents are used.

**6.5.2 Pre-translation PRF.** In the case of CLIR, we can consider two kinds of PRF, pre-translation PRF and post-translation PRF. The pre-translation PRF needs an additional corpus in the source language and it is expected that pre-translation PRF pick up related terms of original query terms before translation process. In the NTCIR-4 CLIR task, the combination of pre- and post-translation expansions is used by the KUNLP group [15] (K to E runs) and UCNTC group [3] (C to E runs).

**6.5.3 Expansion by statistical thesaurus.** The FJUIR group [4] attempts to generate an automatically thesaurus based on term co-occurrence statistics, and to apply it for query expansion. They compare the performance between expansion by automatic thesaurus (“global expansion”) and PRF (“local expansion”).

**6.5.4 Using knowledge ontology.** The I2R group [6] has built knowledge ontology for some short query terms by using a search engine on the Internet with manual verification. The knowledge ontology appears to include narrower terms, related terms and so on. They combine information from the ontology with that from PRF to expand query terms.

### 6.6 Merging strategies

For executing MLIR, we have to extract a single document list from heterogeneous collections consisting of documents written in various languages. One method is to merge lists of individual language, i.e., to integrate search results from BLIR runs against each language part. In the NTCIR4 CLIR task, the following merging strategies are employed:

- *round-robin* strategy (UCNTC group [3] and UniNE group [21])
- *raw-score* merging (UniNE group [21] and IFLAB group [2])
- *normalized-score method* (OKI group [7] and UniNE group [21])
- *Z-score* (UniNE group [21])
- *normalized-by-top-k* strategy (NTU group [30])

In particular, the UniNE group [21] compares the performance between various merging strategies.

### 6.7 Others

**6.7.1 Evaluation techniques.** The UniNE group [21] employs its own method, a bootstrap approach, for examining statistical validation. The TSB group [26] uses its own new evaluation metrics, *Q-measure* and *R-measure*, which can evaluate search performance by directly using multi-grade relevance judgments.

**6.7.2 Effects of translation quality.** Japanese task organizers are taking part in the NTCIR-4 CLIR task as a special group (the NII group [31]), with the purpose of empirically clarifying the influences of translation quality on retrieval performance. They executed a regression analysis using data obtained from three BLIR runs (C-J, K-J and E-J) and a monolingual run (J-J), and showed that the performance of CLIR can be well predicted from two independent variables: quality of translation and difficulty of the topic.

## 7 Search Results and Performance

In this section, we discuss the performance of runs submitted by participants. Recall-precision curves of top-ranked groups (up to eight groups) are shown in Appendix 3.

### 7.1 SLIR runs

**7.1.1 C-C runs.** In total, 52 C-C monolingual runs were submitted by 13 groups (see Table 6). Table 8 shows average, median, maximum and minimum values of mean average precision (MAP) by type of run. We use the following notations:

- C-C: all C-C monolingual runs
- C-C-T: all C-C <TITLE>-only runs (T-runs)
- C-C-D: all C-C <DESC>-only runs (D-runs)
- C-C-O: all runs other than T- or D-runs

**Table 8 MAP of overall C-C runs**

(a) Average and median

	Average		Median	
	Rigid	Relax	Rigid	Relax
C-C	0.1985	0.2471	0.1999	0.2537
C-C-T	0.1943	0.2378	0.1881	0.2356
C-C-D	0.1826	0.2328	0.1741	0.2219
C-C-O	0.2230	0.2762	0.2363	0.2915

(b) Min and max

	Min		Max	
	Rigid	Relax	Rigid	Relax
C-C	0.1251	0.1548	0.3255	0.3880
C-C-T	0.1327	0.1638	0.3146	0.3799
C-C-D	0.1251	0.1548	0.3255	0.3880
C-C-O	0.1461	0.1774	0.2556	0.3103

**Table 9 Top-ranked 8 groups (C-C, Rigid, D-runs)**

Run-ID	MAP
I2R-C-C-D-01	0.3255
OKI-C-C-D-04	0.2274
pircs-C-C-D-02	0.2150
RCUNA-C-C-D-01	0.2087
UniNE-C-C-D-03	0.2011
KLE-C-C-D-01	0.1990
IFLAB-C-C-D-01	0.1920
JSCCC-C-C-D-03	0.1886

Table 9 shows the top eight groups ranked according to MAP values of D-runs based on rigid relevance. I2R-C-C-D-01 based on ontological query expansion is dominant. There are almost no statistically significant differences between the other seven groups.

**7.1.2 J-J runs.** In total, 58 J-J monolingual runs were

submitted by 14 groups (see Table 6). Table 10 shows average, median, maximum and minimum values of mean average precision (MAP) by type of run. Table 11 indicates the top eight groups ranked according to MAP values of D-runs based on rigid relevance.

**Table 10 MAP of overall J-J runs**

(a) Average and median

	Average		Median	
	Rigid	Relax	Rigid	Relax
J-J	0.3258	0.4247	0.3358	0.4329
J-J-T	0.3114	0.4073	0.3135	0.4112
J-J-D	0.3227	0.4212	0.3352	0.4295
J-J-O	0.3441	0.4467	0.3487	0.4622

(b)Min and max

	Min		Max	
	Rigid	Relax	Rigid	Relax
J-J	0.1966	0.2759	0.3915	0.4963
J-J-T	0.1966	0.2759	0.3890	0.4864
J-J-D	0.2130	0.2951	0.3804	0.4838
J-J-O	0.2663	0.3477	0.3915	0.4963

**Table 11 Top-ranked 8 groups (J-J, Rigid, D-runs)**

Run-ID	MAP
PLLS-J-J-D-04	0.3804
JSCCC-J-J-D-01	0.3747
RCUNA-J-J-D-01	0.3680
TSB-J-J-D-01	0.3667
CRL-J-J-D-02	0.3612
UniNE-J-J-D-02	0.3484
KLE-J-J-D-01	0.3352
BRKLY-J-J-D-02	0.3223

**Table 12 MAP of overall K-K runs**

(a) Average and median

	Average		Median	
	Rigid	Relax	Rigid	Relax
K-K	0.4109	0.4402	0.4431	0.4699
K-K-T	0.4271	0.4582	0.4588	0.4934
K-K-D	0.3869	0.4149	0.3727	0.3992
K-K-O	0.4171	0.4457	0.4694	0.5004

(b)Min and max

	Min		Max	
	Rigid	Relax	Rigid	Relax
K-K	0.0000	0.0000	0.5825	0.6212
K-K-T	0.2821	0.3136	0.5078	0.5361
K-K-D	0.2297	0.2587	0.4685	0.5097
K-K-O	0.0000	0.0000	0.5825	0.6212

**7.1.3 K-K runs.** In total, 31 K-K monolingual runs were submitted by eight groups (see Table 6). Table

12 shows average, median, maximum and minimum values of mean average precision (MAP) by type of run. Table 13 indicates top the eight groups ranked according to MAP values of D-runs based on rigid relevance.

**7.1.4 E-E runs.** In total, 41 E-E monolingual runs were submitted by 10 groups (see Table 6). Table 14 shows average, median, maximum and minimum values of mean average precision (MAP) by type of run. Table 15 indicates the top eight groups ranked according to MAP values of D-runs based on rigid relevance.

**Table 13 Top-ranked 8 groups (K-K, Rigid, D-runs)**

Run-ID	MAP
CRL-K-K-D-02	0.4685
KLE-K-K-D-01	0.4617
UniNE-K-K-D-05	0.4431
pircs-K-K-D-02	0.3777
HUM-K-K-D-05	0.3677
IFLAB-K-K-D-01	0.3675
FJUIR-K-K-D-02	0.3646
tlrrd-K-K-D-02	0.2297

**Table 14 MAP of overall E-E runs**

(a) Average and median

	Average		Median	
	Rigid	Relax	Rigid	Relax
E-E	0.3102	0.3908	0.3161	0.4042
E-E-T	0.2963	0.3767	0.3145	0.3954
E-E-D	0.2895	0.3676	0.3026	0.3859
E-E-O	0.3518	0.4357	0.3573	0.4423

(b)Min and max

	Min		Max	
	Rigid	Relax	Rigid	Relax
E-E	0.0342	0.0483	0.4000	0.4962
E-E-T	0.0802	0.1032	0.3576	0.4512
E-E-D	0.0342	0.0483	0.3469	0.4368
E-E-O	0.2864	0.3627	0.4000	0.4962

**Table 15 Top-ranked 8 groups (E-E, Rigid, D-runs)**

Run-ID	MAP
TSB-E-E-D-01	0.3469
JSCCC-E-E-D-04	0.3382
OKI-E-E-D-04	0.3286
UniNE-E-E-D-04	0.3169
pircs-E-E-D-02	0.3055
CRL-E-E-D-02	0.2997
HUM-E-E-D-05	0.2990
IFLAB-E-E-D-01	0.2953

**7.1.5 Remarks.** The average values of MAP of all C-C runs, all J-J runs, all K-K runs and all E-E runs

based on rigid relevance are 0.1985, 0.3258, 0.4109, and 0.3102, respectively (see Table 8, 10, 12 and 14). Chinese monolingual runs appear to be more difficult than the other languages, and Korean monolingual runs easier.

## 7.2 BLIR runs on Chinese document set

**7.2.1 J-C runs.** In total, 8 J-C runs were submitted by only two groups (see Table 6). Table 16 shows the best runs of each group (only D-runs based on rigid relevance). While IFLAB uses standard bilingual resources (dictionary and corpus-based), OKI applies the pivot language method. As shown in Table 16, the MAP values of J-C runs are not high.

**Table 16 Best runs of each group (J-C, Rigid, D-runs)**

Run-ID	MAP
IFLAB-J-C-D-01	0.0548
OKI-J-C-D-04 (pivot)	0.0404

**7.2.2 K-C runs.** Only one group submitted search results of K-C runs (5 runs were submitted). The best run is KLE-K-C-D-01, of which the MAP value is 0.1447.

**7.2.3 E-C runs.** In total, 12 E-C runs were submitted by three groups (see Table 6). Table 17 shows the best runs of each group (only D-runs based on rigid relevance). As similar with J-C runs, the performance is low.

**Table 17 Best runs of each group (E-C, Rigid, D-runs)**

Run-ID	MAP
TJUCN-E-C-D-01	0.0663
OKI-E-C-D-04	0.0481
ISCAS-E-C-D-03	0.0017

**7.2.4 Remarks.** The values of MAP in J-C and E-C runs are low and so further research is required. Meanwhile, KLE runs show better performance in K-C retrieval. Values of MAP of the best J-C run, the best K-C run and the best E-C run (D-runs) are 0.0548, 0.1447, and 0.0663, respectively, and these MAP values are 16.8%, 44.4% and 20.4% of that of the best C-C run (0.3255, rigid and D-runs), respectively.

## 7.3 BLIR runs on Japanese document set

**7.3.1 C-J runs.** In total, 18 C-J runs were submitted by five groups (see Table 6). Table 18 shows the best runs of each group (only D-runs based on rigid relevance). While TSB and NII use MT systems, the other three groups, BRKLY, OKI and tlrrd, adopt the pivot language approach. Only the performance of

BRKLY using the MT system-based pivot approach is comparable with that of the non-pivot approach (especially, the BRKLY run outperforms the NII run).

**7.3.2 K-J runs.** In total, 13 K-J runs were submitted by four groups (see Table 6). Table 19 shows the best runs of each group (only <DESC>-only run based on rigid relevance). While KLE and NII use direct bilingual resources, the other two groups, BRKLY and tlrrd, adopt the pivot language approach. The performance of the pivot language approach does not reach that of the non-pivot approach.

**Table 18 Best runs of each group (C-J, Rigid, D-runs)**

Run-ID	MAP
TSB-C-J-D-03	0.2309
BRKLY-C-J-D-03	0.1904
NII-C-J-D-02	0.1455
OKI-C-J-D-04	0.1088
tlrrd-C-J-D-02	0.0544

**Table 19 Best runs of each group (K-J, Rigid, D-runs)**

Run-ID	MAP
KLE-K-J-D-01	0.2935
NII-K-J-D-02	0.1894
BRKLY-K-J-D-03	0.1402
tlrrd-K-J-D-02	0.0964

**7.3.3 E-J runs.** In total, 15 E-J runs were submitted by four groups (see Table 6). Table 20 shows the best runs of each group (only D-runs based on rigid relevance). While TSB and NII use direct MT systems, the other two groups, OKI and BRKLY, adopt the pivot language approach. OKI's run outperforms the runs by the non-pivot, direct translation approach.

**Table 20 Best runs of each group (E-J, Rigid, D-runs)**

Run-ID	MAP
OKI-E-J-D-04	0.2674
TSB-E-J-D-01	0.2672
NII-E-J-D-02	0.2533
BRKLY-E-J-D-02	0.1874

**7.3.4 Remarks.** Values of MAP of the best C-J runs, the best K-J run and the best E-J run (D-runs) are 0.2309, 0.2935, and 0.2674, respectively, and these MAP values are 60.7%, 77.2% and 70.3% of that of the best J-J run (0.3804, rigid and D-runs), respectively. The pivot language approach shows comparable performance with the non-pivot, direct translation approach in C-J and E-J runs.

## 7.4 BLIR runs on Korean document set

**7.4.1 C-K runs.** In total, eight C-K runs were sub-

mitted by only two groups (see Table 6). Table 21 shows the best runs of each group (only D-runs based on rigid relevance). The pircs run adopts the pivot language approach, and its performance is lower than that of the KLE run using the direct translation approach.

**Table 21 Best runs of each group (C-K, Rigid, D-runs)**

Run-ID	MAP
KLE-C-K-D-01	0.3973
pircs-C-K-D-02	0.2471

**7.4.2 J-K runs.** In total, eight J-K runs were submitted by only two groups (see Table 6). Table 22 shows the best runs of each group (only D-runs based on rigid relevance).

**Table 22 Best runs of each group (J-K, Rigid, D-runs)**

Run-ID	MAP
KLE-J-K-D-01	0.3984
IFLAB-J-K-D-01	0.2363

**7.4.3 E-K runs.** In total, seven E-K runs were submitted by only two groups (see Table 6). Table 23 shows the best runs of each group (only D-runs based on rigid relevance).

**Table 23 Best runs of each group (E-K, Rigid, D-runs)**

Run-ID	MAP
pircs-E-K-D-02	0.3249
KLE-E-K-D-01	0.0981

**7.4.4 Remarks.** Values of MAP of the best C-K run, the best J-K run and the best E-K run (D-runs) are 0.3973, 0.3984, and 0.3249, respectively, and these MAP values are 84.8%, 85.0% and 69.3% of that of the best K-K run (0.4685, rigid and D-runs), respectively.

**Table 24 Best runs of each group (C-E, Rigid, D-runs)**

Run-ID	MAP
pircs-C-E-D-02	0.2238
TSB-C-E-D-01	0.2183
RMIT-C-E-D-04	0.1918
UCNTC-C-E-D-02	0.1758
JSCCC-C-E-D-01	0.1575
OKI-C-E-D-04	0.1265
AILAB-C-E-D-01	0.0412

## 7.5 BLIR runs on English document set

**7.5.1 C-E runs.** In total, 24 C-E runs were submitted by seven groups (see Table 6). Table 24 shows the best runs of each group (only D-runs based on rigid

relevance). The TSB run was executed using Japanese as a pivot (by two MT systems). The TBS and pircs employ the MT system and the other five runs are based on bilingual dictionaries.

**7.5.2 J-E runs.** In total, 23 J-E runs were submitted by six groups (see Table 6). Table 25 shows the best runs of each group (only D-runs based on rigid relevance). The TBS run and the OKI run were executed using the MT system (OKI also employs parallel corpus and a bilingual dictionary) and for the other four runs, no MT system seems to be used.

**7.5.3 K-E runs.** In total, eight K-E runs were submitted by only two groups (see Table 6). Table 26 shows the best runs of each group (only D-runs based on rigid relevance).

**Table 25 Best runs of each group (J-E, Rigid, D-runs)**

Run-ID	MAP
TSB-J-E-D-01	0.3340
OKI-J-E-D-04	0.2813
JSCCC-J-E-D-02	0.2620
IFLAB-J-E-D-01	0.2225
FORES-J-E-D-01	0.0775
UENIS-J-E-D-02	0.0075

**Table 26 Best runs of each group (K-E, Rigid, D-runs)**

Run-ID	MAP
KUNLP-K-E-D-02	0.2250
KLE-K-E-D-01	0.1876

**7.5.4 Remarks.** Values of MAP of the best C-E run, the best J-E run and the best K-E run (D-runs) are 0.2238, 0.3340, and 0.2250, respectively, and these MAP values are 64.5%, 96.2%, and 64.9% of that of the best E-E run (0.3469, rigid and D-runs), respectively. Especially, the top E-J run shows almost the same performance as the best E-E monolingual run.

**Table 27 Best runs of each group by run type (MLIR, Rigid, D-runs)**

Run-ID	MAP
C-CEJ: OKI-C-CEJ-D-04	0.0923
NTU-C-CJE-D-01	0.0521
J-CEJ: OKI-J-CEJ-D-04	0.1566
E-CJE: UniNE-E-CJE-D-02	0.1604
OKI-E-CEJ-D-04	0.1588
UCNTC-E-CJE-D-02	0.0877
J-CJKE: IFLAB-J-CJKE-D-01	0.1296
E-CJKE: UniNE-E-CJKE-D-03*	0.1766

\*It should be noted that UniNE-E-CJKE-D-03 includes a search on the Korean collection based on the DNC topic sections.

## 7.6 MLIR

In the case of MLIR on the CJE collection, nine C-CJE runs submitted by two groups, five J-CJE runs by one group, and 15 E-CJE runs by three groups (see Table 6). For MLIR on the larger CJKE collection, three J-CJKE runs were submitted by one group and five E-CJKE runs by one group. Table 27 shows the best runs of each group by run type (only D-runs based on rigid relevance).

## 8 Concluding remarks

A greater number of approach and techniques are being investigated in this task than before, such as various Chinese indexing methods, transliteration techniques, Web-based solutions for the out-of-vocabulary problem, applications of LM, new challenges to query expansion, and so on. However, there is a room for further research on improving Chinese information retrieval in comparison with Korean and Japanese IR. In this task, the performance of Korean IR is relatively high, which may be partly because Korean text includes white spaces as delimiters. Further investigation on CLIR between CJK languages is needed.

## References

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**Appendix 1. List of participants**

ID	Name	Country	Runs
AILAB	AI Lab; MIS Dept.; University of Arizona	USA	E-E, C-E
BRKLY	Text Retrieval Research Group; University of California; Berkeley	USA	J-J, K-J, E-J, C-J
CRL	Communications Research Laboratory	Japan	J-J, K-K, E-E
FJUIR	Information Retrieval Laboratory; Fu Jen Catholic University	Taiwan	K-K, C-C, J-J
FORES	Mori Lab.; Yokohama National University	Japan	J-E
HUM	Hummingbird	Canada	C-C, J-J, K-K, E-E
I2R	Natural Language Processing Lab; Institute of Inforcomm Research	Singapore	C-C
IFLAB	University of Tsukuba; Ishikawa-Fujii Laboratory	Japan	C-C, J-J, K-K, E-E, J-C, J-K, J-E, J-CJKE
ISCAS	Institute of Software; Chinese Academy of Sciences	China	C-C, E-C
JSCCC	Clairvoyance Corporation and Justsystem	USA (+ Japan)	C-C, J-J, E-E, C-E, J-E
KLE	Knowledge & Language Engineering Lab.; Pohang University of Science & Technology	Korea	C-C, J-J, K-K, E-E, K-C, K-J, C-K, J-K, E-K, K-E
KUNLP	Natural Language Processing Lab.; Korea University	Korea	K-E
NII	National Institute of Informatics	Japan	J-J, C-J, K-J, E-J
NTU	Natural Language Processing Laboratory,	Taiwan	C-CJE

	National Taiwan University		
OKI	Oki Electric Industry	Japan	C-C, J-J, E-E, J-C, E-C, C-J, E-J, C-E, J-E, C-CJE, J-CJE, E-CJE
pircs	City U. New York - Queens	USA	C-C, E-E, E-K, C-E, K-K, C-K
PLLS	PATOLIS Corporation; R&D; IR Project	Japan	J-J
PolyU	Hong Kong Polytechnic University	Hong Kong	C-C
RCUNA	Ubiquitous Solution Lab; Software R&D Group; RICOH COMPANY; LTD	Japan	C-C, J-J
RMIT	RMIT School of Computer Science & IT	Australia	C-E
TJUCN	Artificial Intelligence Laboratory; Tianjin University	Taiwan	E-C
tlrrd	TLR Research & Development Group	USA	C-J, K-J, K-K, C-C, J-J
TSB	Toshiba Corporate R&D Center	Japan	J-J, E-E, C-J, E-J, C-E, J-E
UCNTC	Computer Science; University of Chicago	USA	C-E, E-CJE
UENIS	Uemura Laboratory; Nara Institute of Science and Technology	Japan	J-E
UniNE	University of Neuchatel	Switzerland	C-C, J-J, K-K, E-E, E-CJE, E-CJKE

**Appendix 2. Numbers of relevant documents**

topic	C		K		J		E		CJE		CJKE	
	S+A	S+A+B	S+A	S+A+B	S+A	S+A+B	S+A	S+A+B	S+A	S+A+B	S+A	S+A+B
001	28	46	0	0	0	0	1	8	29	54	29	54
002	17	24	13	13	1	1	5	6	23	31	36	44
003	16	22	33	35	22	44	14	24	52	90	85	125
004	15	23	15	21	6	15	12	33	33	71	48	92
005	7	13	94	98	38	60	14	20	59	93	153	191
006	16	31	26	29	11	15	16	21	43	67	69	96
007	7	16	10	10	12	12	17	21	36	49	46	59
008	26	56	61	72	21	26	15	19	62	101	123	173
009	3	4	171	185	20	23	9	28	32	55	203	240
010	6	8	0	8	55	73	45	51	106	132	106	140
011	27	47	2	2	25	70	14	31	66	148	68	150
012	8	15	4	6	52	61	16	20	76	96	80	102
013	12	14	4	4	120	178	17	23	149	215	153	219
014	14	19	67	77	105	182	22	44	141	245	208	322
015	38	60	129	168	78	126	363	640	479	826	608	994
016	27	49	37	117	88	330	110	267	225	646	262	763
017	30	68	27	48	49	115	19	220	98	403	125	451
018	61	77	13	22	301	391	158	352	520	820	533	842
019	28	45	83	98	204	239	253	441	485	725	568	823
020	16	30	121	129	349	358	38	283	403	671	524	800
021	17	21	22	34	16	23	47	101	80	145	102	179
022	4	7	109	132	2	3	23	60	29	70	138	202
023	28	42	30	53	153	160	11	72	192	274	222	327
024	46	57	120	140	83	136	34	174	163	367	283	507
025	0	6	118	125	2	2	28	55	30	63	148	188
026	26	33	43	76	63	71	34	77	123	181	166	257
027	43	74	18	26	62	70	30	78	135	222	153	248



028	8	12	17	22	56	70	14	38	78	120	95	142
029	22	46	86	108	67	174	34	55	123	275	209	383
030	38	65	84	115	95	143	56	180	189	388	273	503
031	45	52	129	156	159	159	198	520	402	731	531	887
032	14	17	18	28	80	80	9	22	103	119	121	147
033	11	30	60	144	132	181	35	352	178	563	238	707
034	15	24	4	4	60	182	29	52	104	258	108	262
035	55	62	7	22	335	361	210	337	600	760	607	782
036	19	34	39	43	66	119	497	589	582	742	621	785
037	13	28	67	82	253	371	212	324	478	723	545	805
038	5	17	32	34	0	39	1	14	6	70	38	104
039	39	55	27	33	58	85	90	147	187	287	214	320
040	7	9	18	20	90	130	28	37	125	176	143	196
041	14	21	57	76	94	108	76	91	184	220	241	296
042	20	28	27	30	56	75	34	34	110	137	137	167
043	24	38	103	103	173	330	31	35	228	403	331	506
044	43	65	121	132	448	645	410	1072	901	1782	1022	1914
045	47	66	110	122	94	495	79	318	220	879	330	1001
046	13	20	50	76	37	138	36	48	86	206	136	282
047	19	33	41	46	128	414	642	823	789	1270	830	1316
048	17	21	36	38	76	169	55	86	148	276	184	314
049	24	46	67	78	195	305	207	310	426	661	493	739
050	30	52	36	76	299	418	179	295	508	765	544	841
051	13	18	24	24	58	80	119	127	190	225	214	249
052	3	6	3	3	179	221	23	40	205	267	208	270
053	17	35	36	36	45	102	21	99	83	236	119	272
054	45	78	50	52	375	646	283	366	703	1090	753	1142
055	21	27	48	55	328	672	263	299	612	998	660	1053
056	18	27	68	76	135	318	100	194	253	539	321	615
057	25	36	93	108	548	719	225	356	798	1111	891	1219
058	27	36	43	53	109	174	96	137	232	347	275	400
059	19	39	110	143	233	379	81	228	333	646	443	789
060	22	41	52	61	143	233	130	284	295	558	347	619

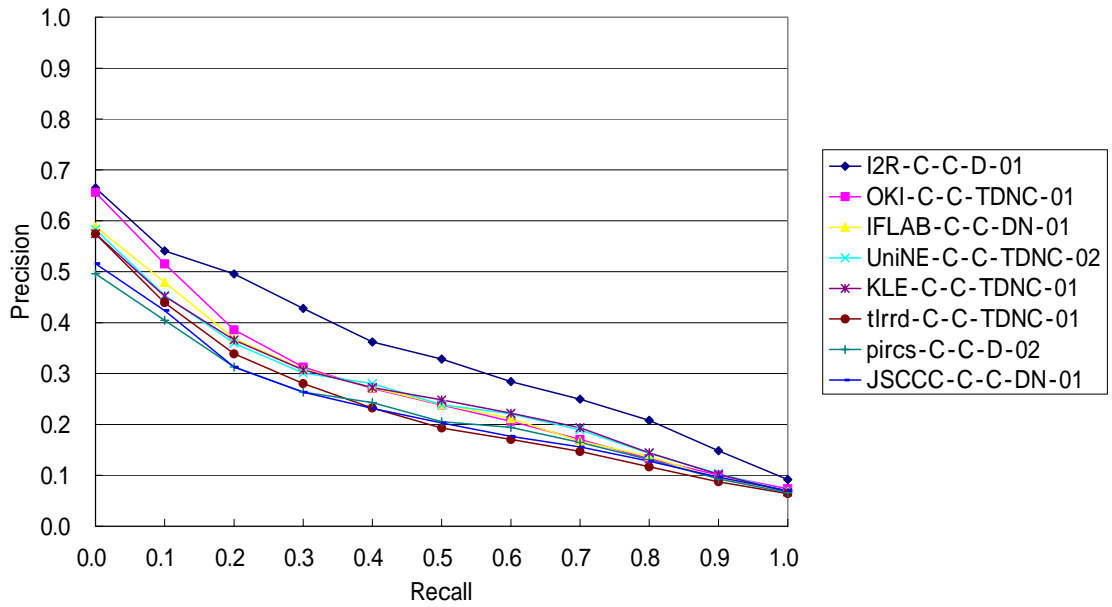
### Appendix 3. Recall-precision curves by type of runs

The following recall-precision graphs show top-ranked runs according to MAP values by type of runs. For example,

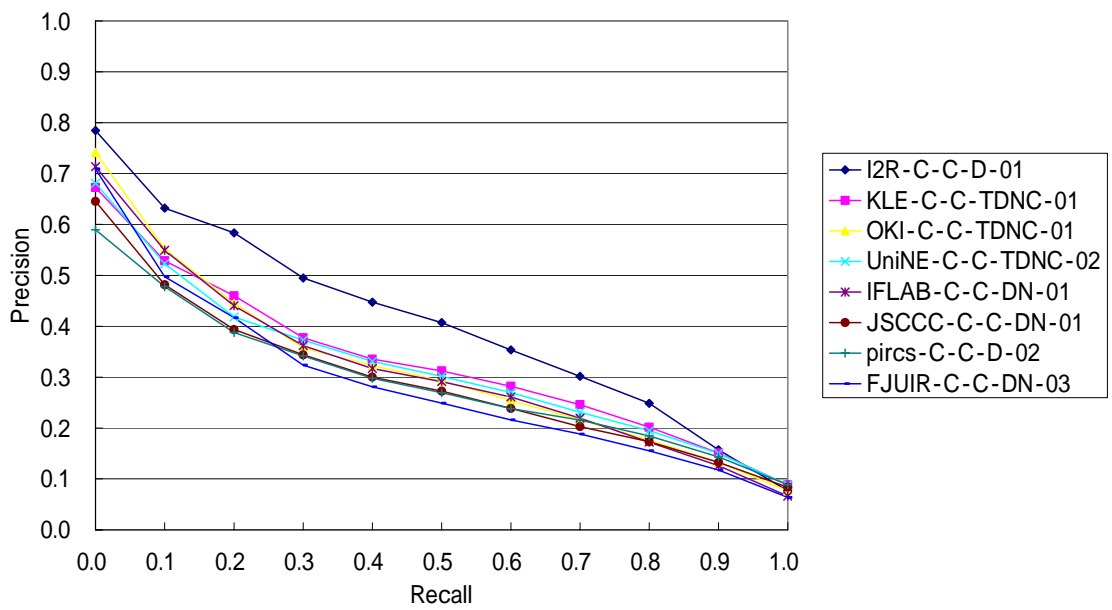
- C-C: all C-C monolingual runs
- C-C-T: all C-C <TITLE>-only runs (T-runs)
- C-C-D: all C-C <DESC>-only runs (D-runs)
- C-C-O: all other runs than T- or D-runs

It should be noted that only the best run of each research group is picked up by types of runs, and that each page includes two graphs, i.e., one is based on rigid relevance and the other relaxed relevance.

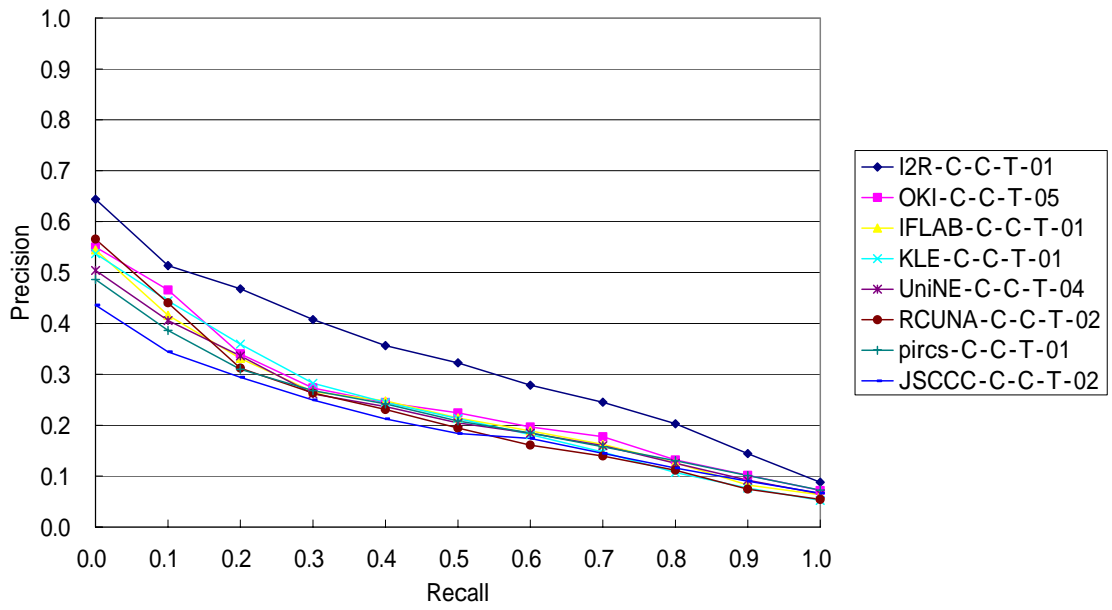
C-C(Rigid)



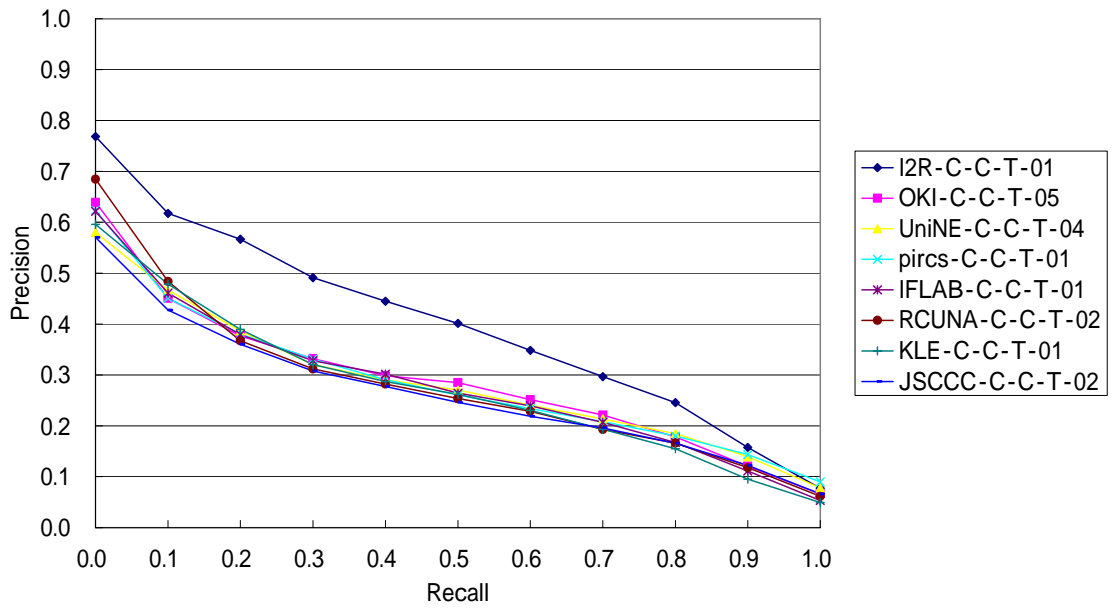
C-C(Relax)



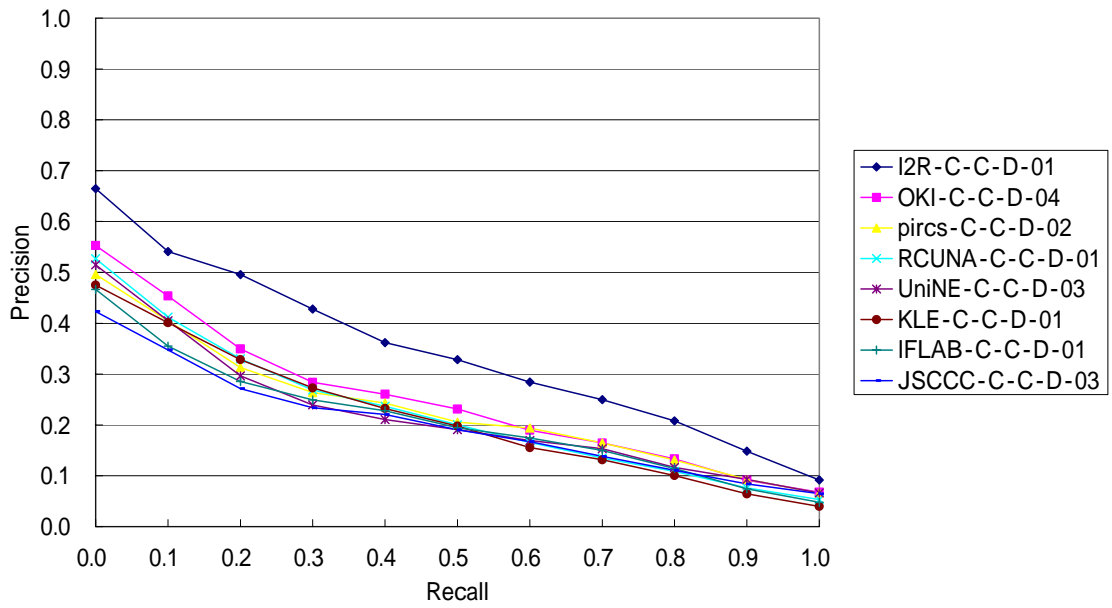
C-C-T(Rigid)



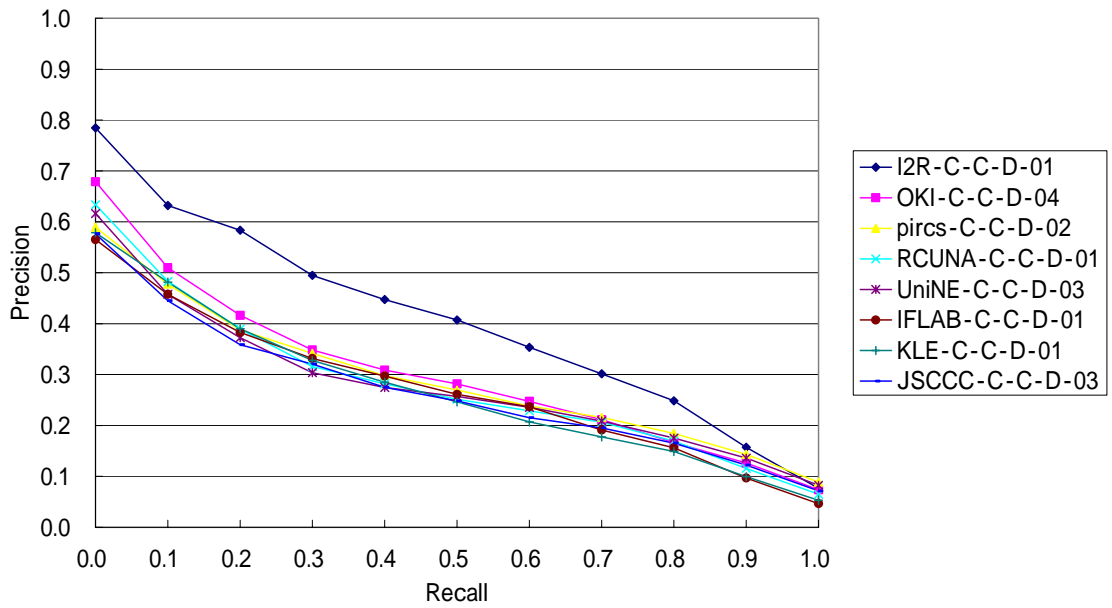
C-C-T(Relax)



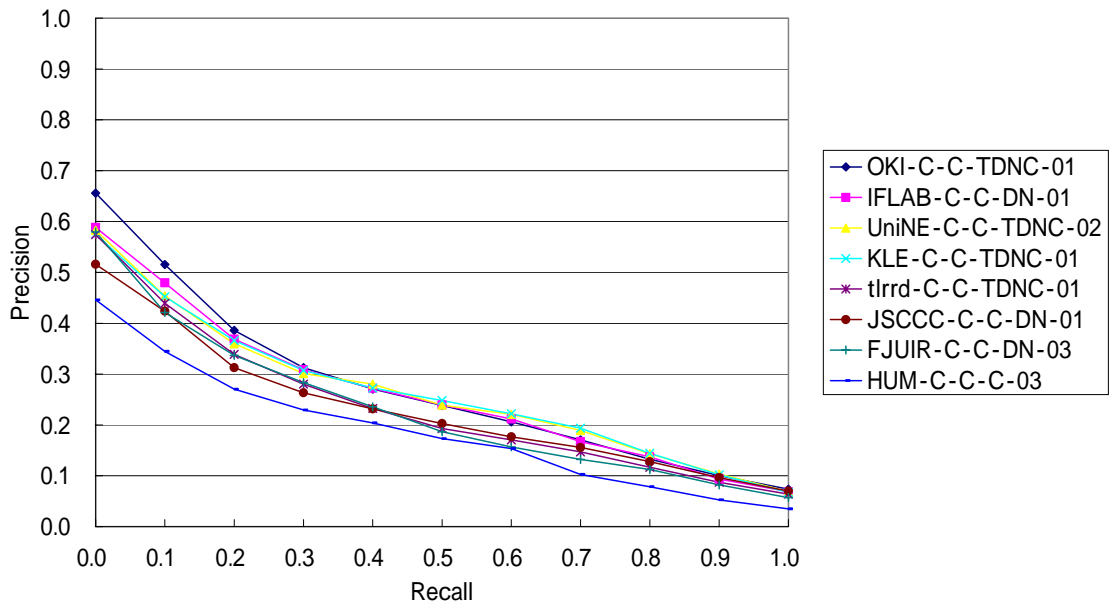
C-C-D(Rigid)



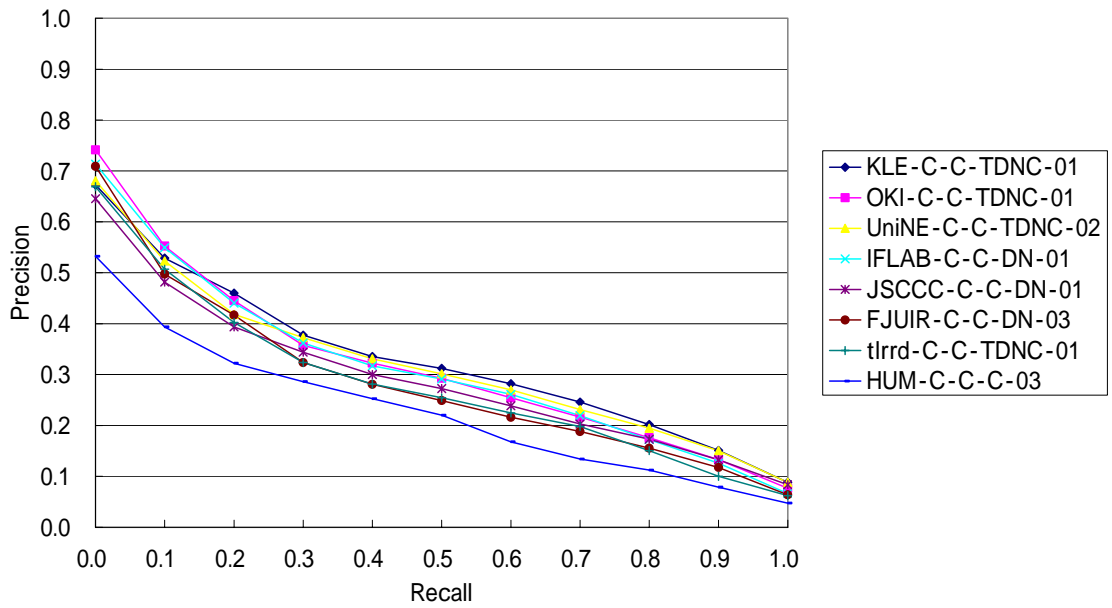
C-C-D(Relax)



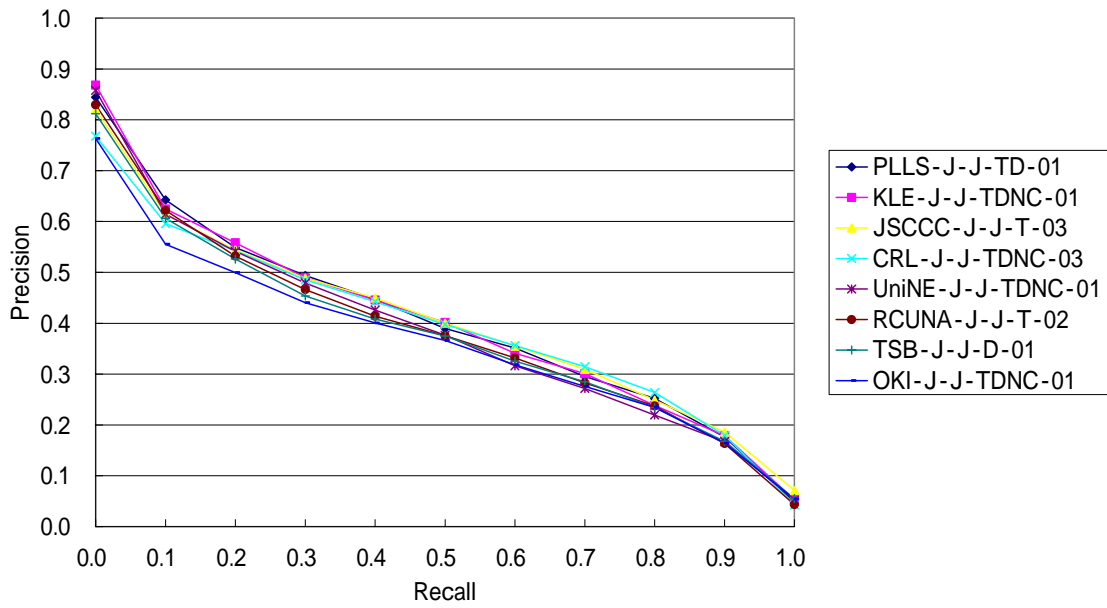
C-C-O(Rigid)



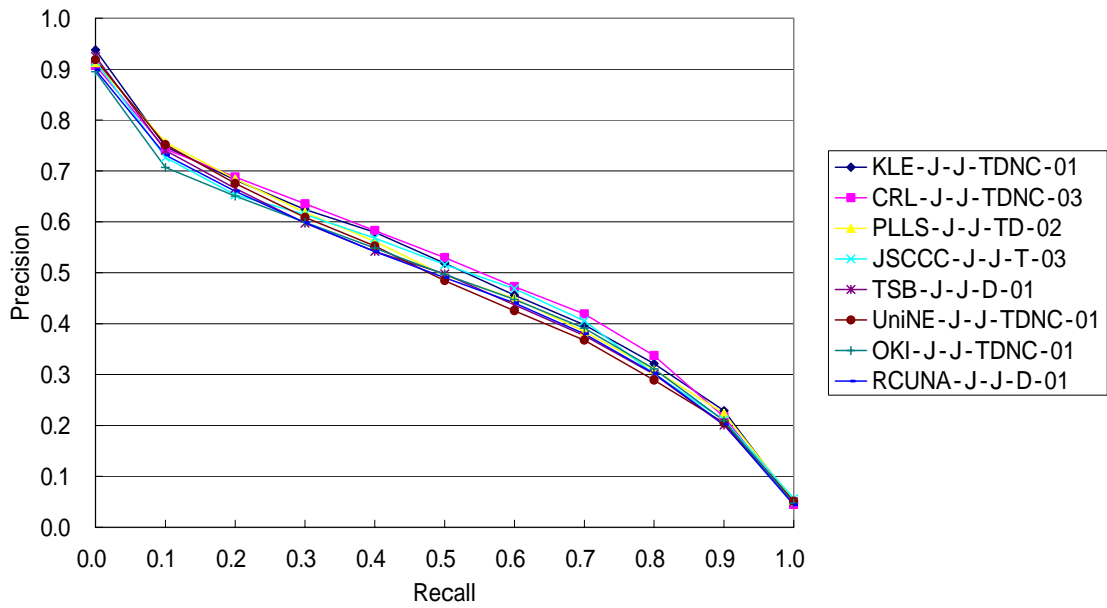
C-C-O(Relax)



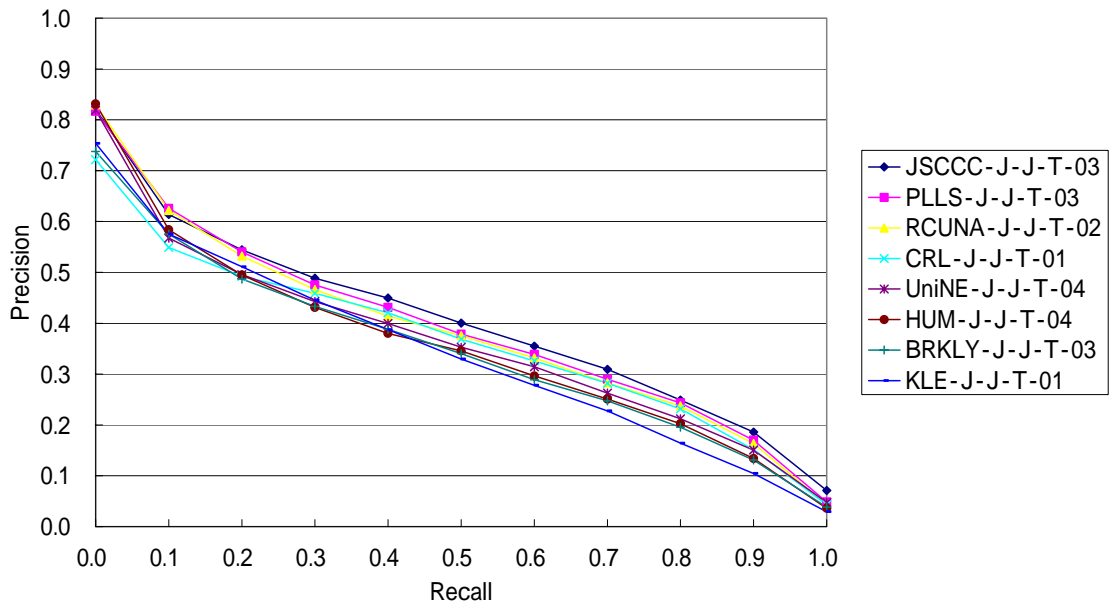
J-J(Rigid)



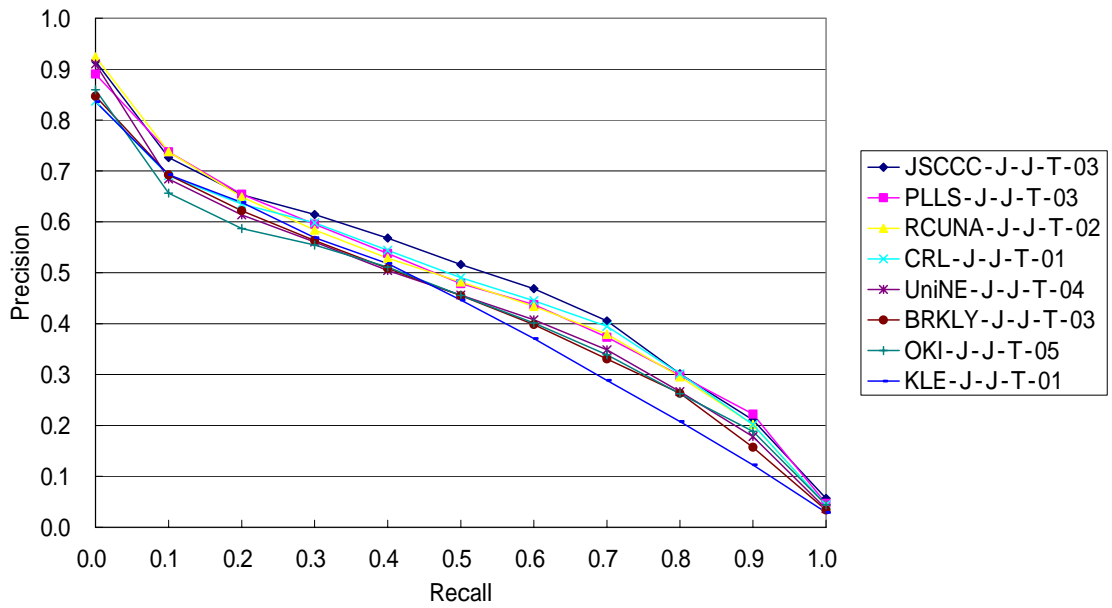
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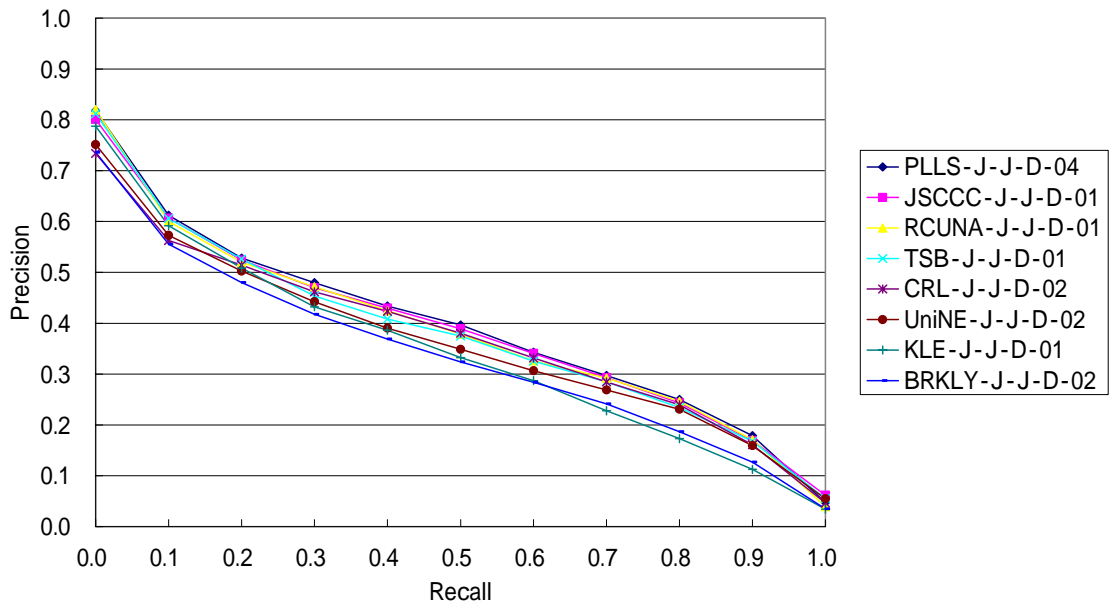
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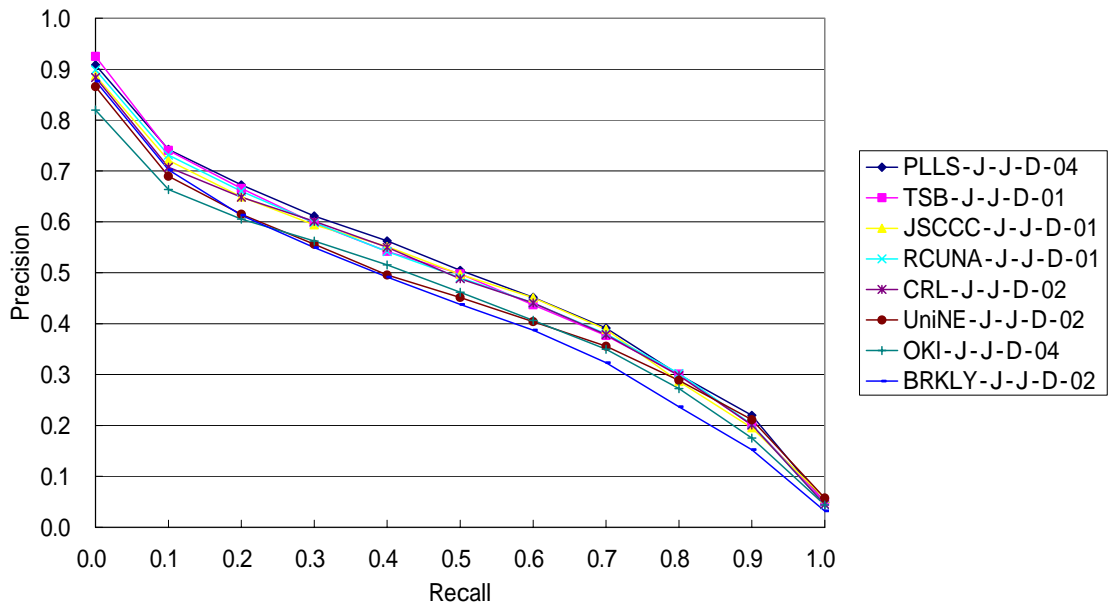
J-J-T(Relax)



J-J-D(Rigid)

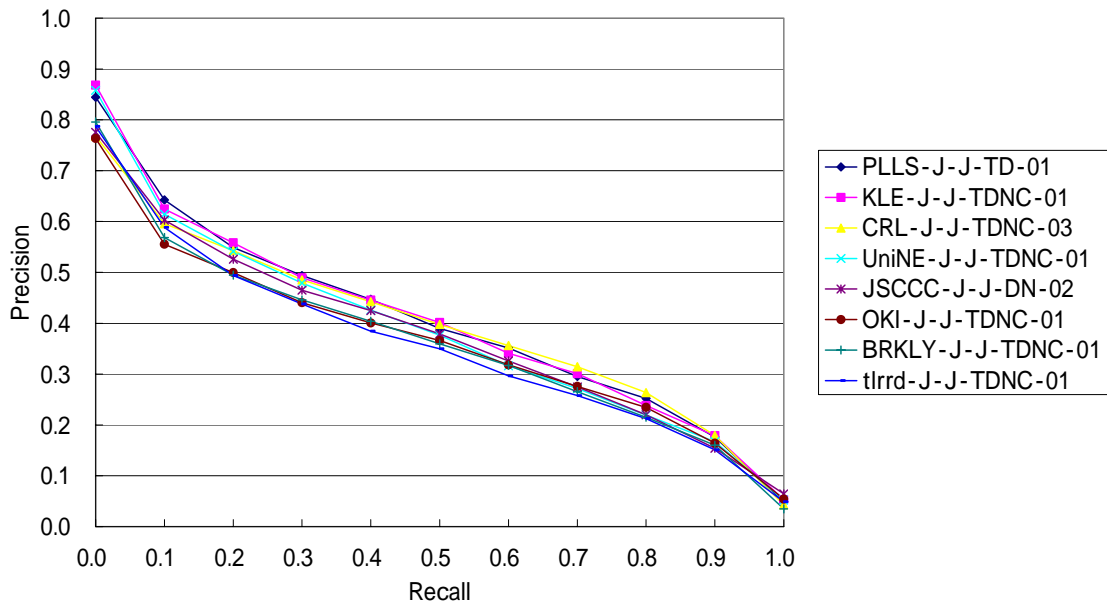


J-J-D(Relax)

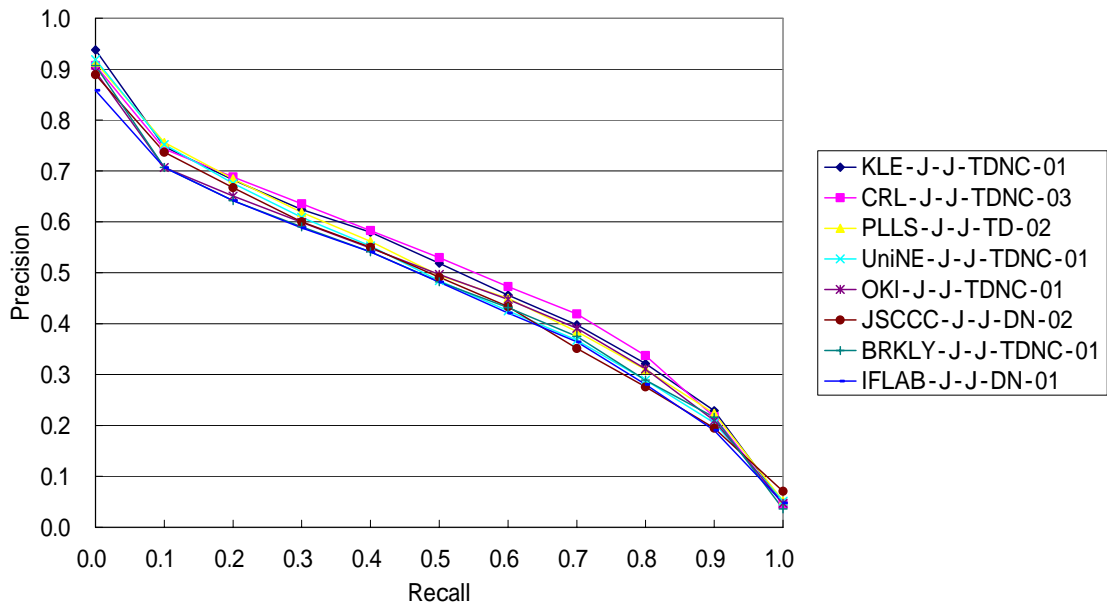




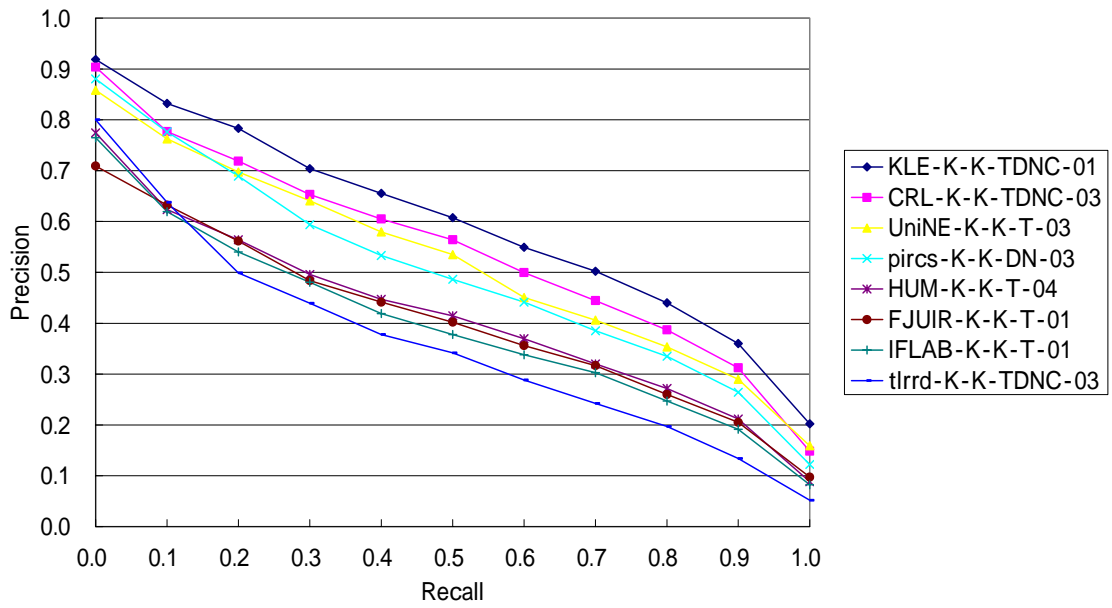
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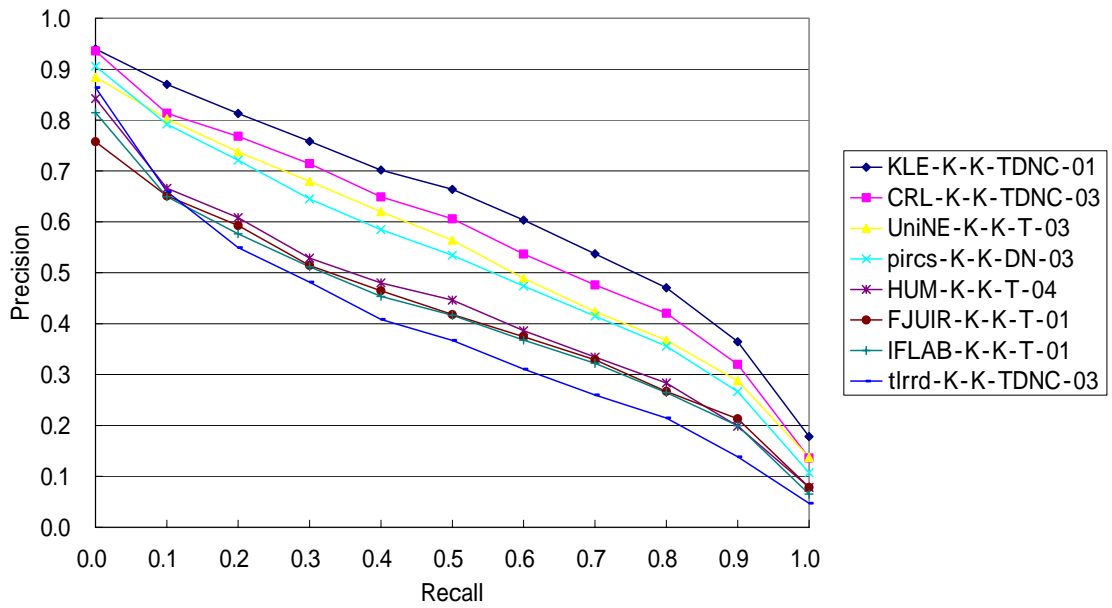
J-J-O(Relax)



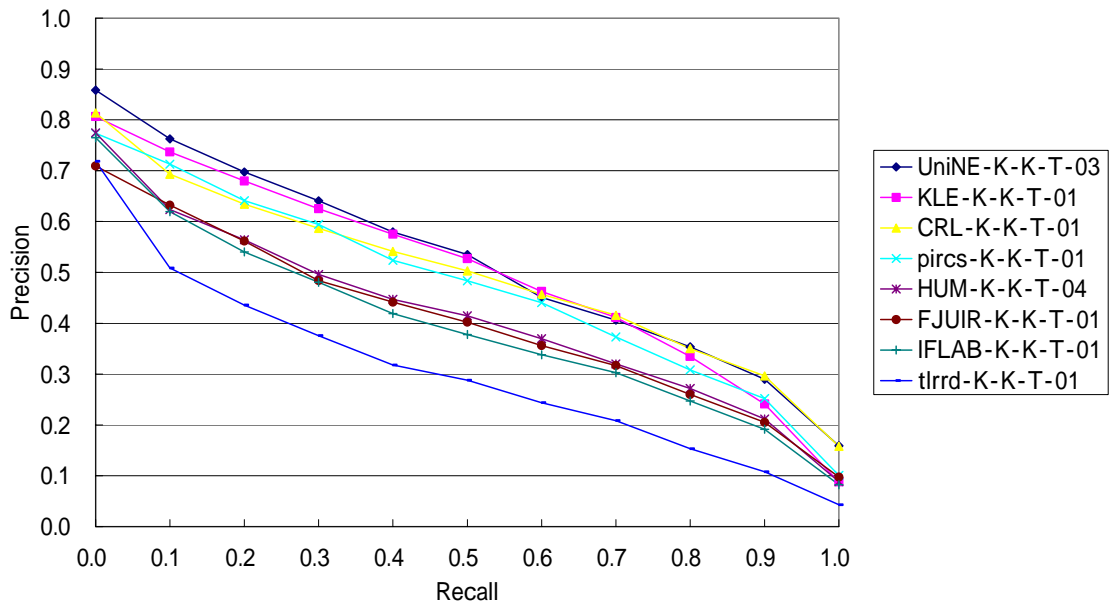
K-K(Rigid)



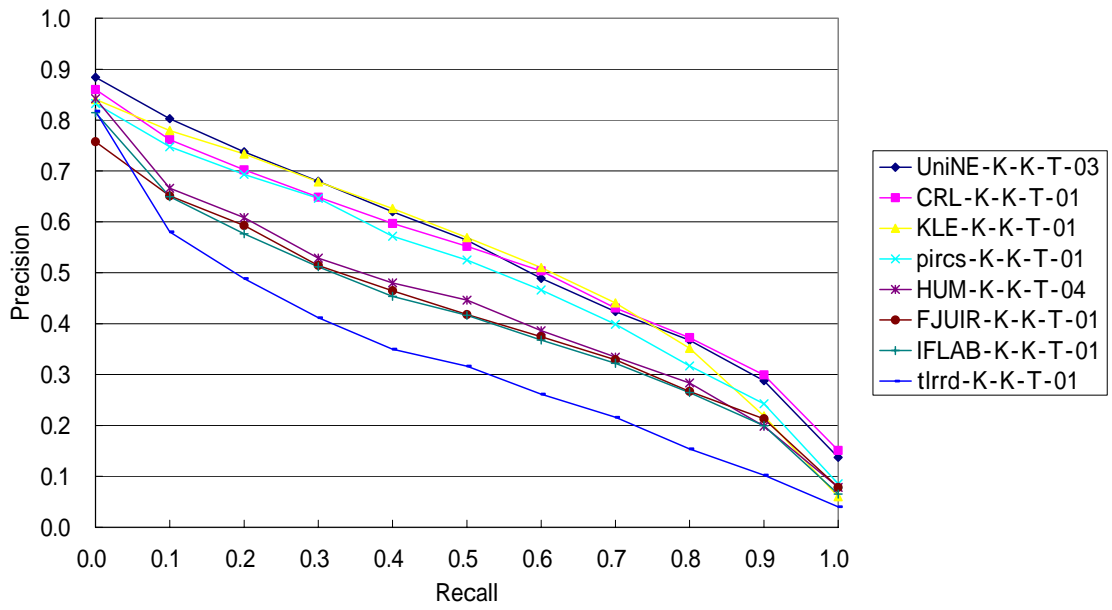
K-K(Relax)



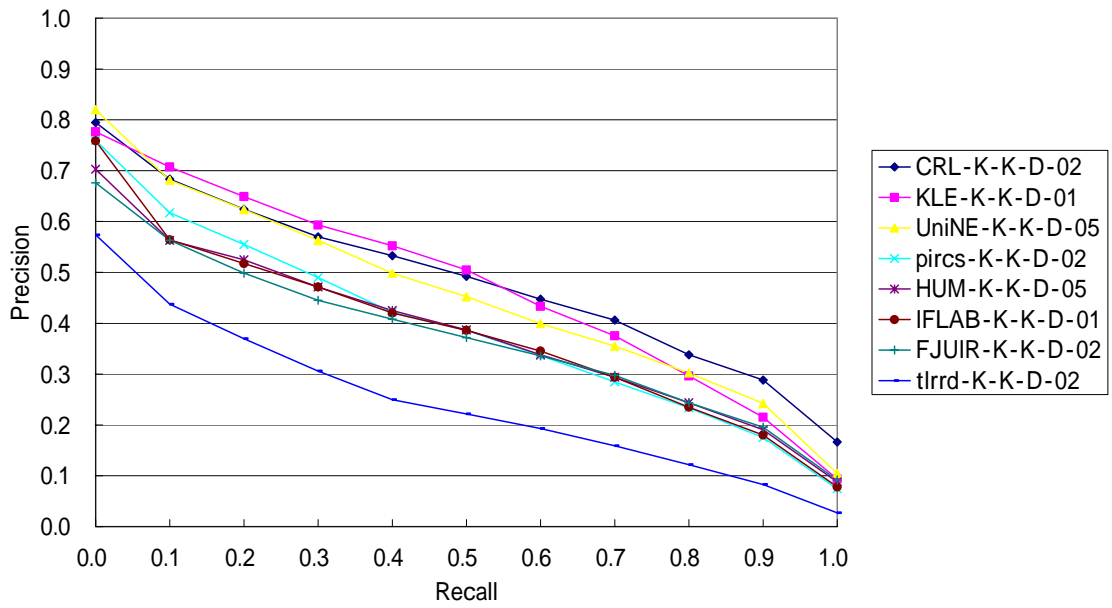
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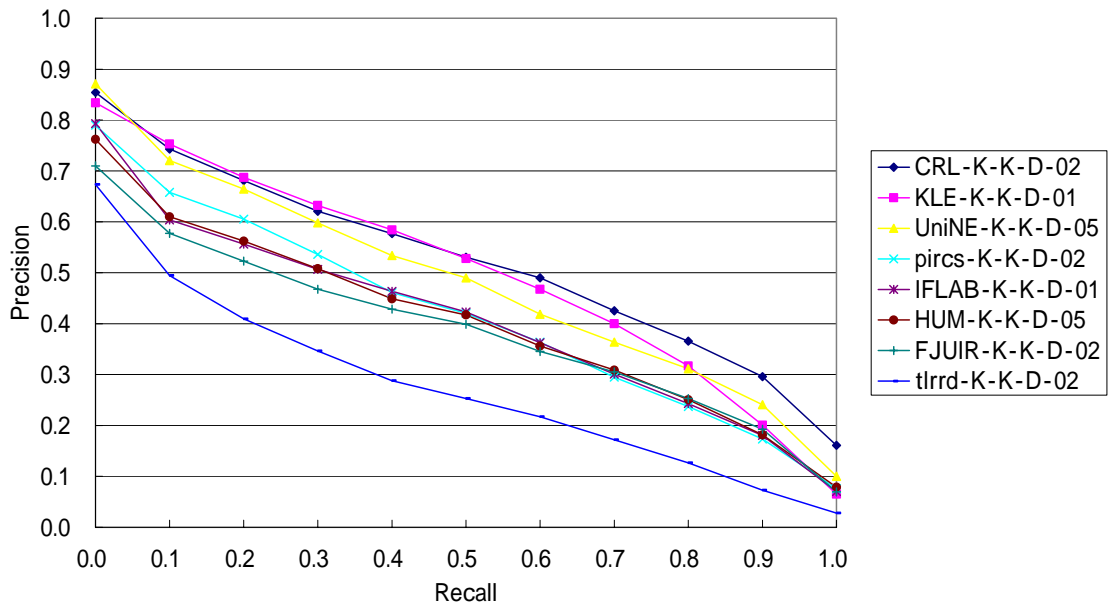
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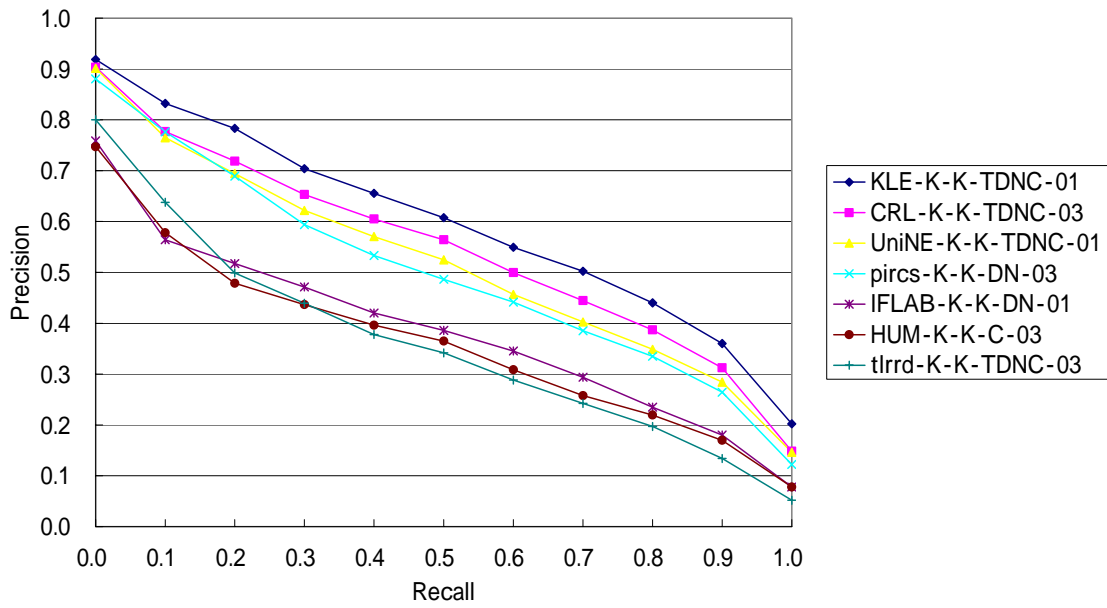
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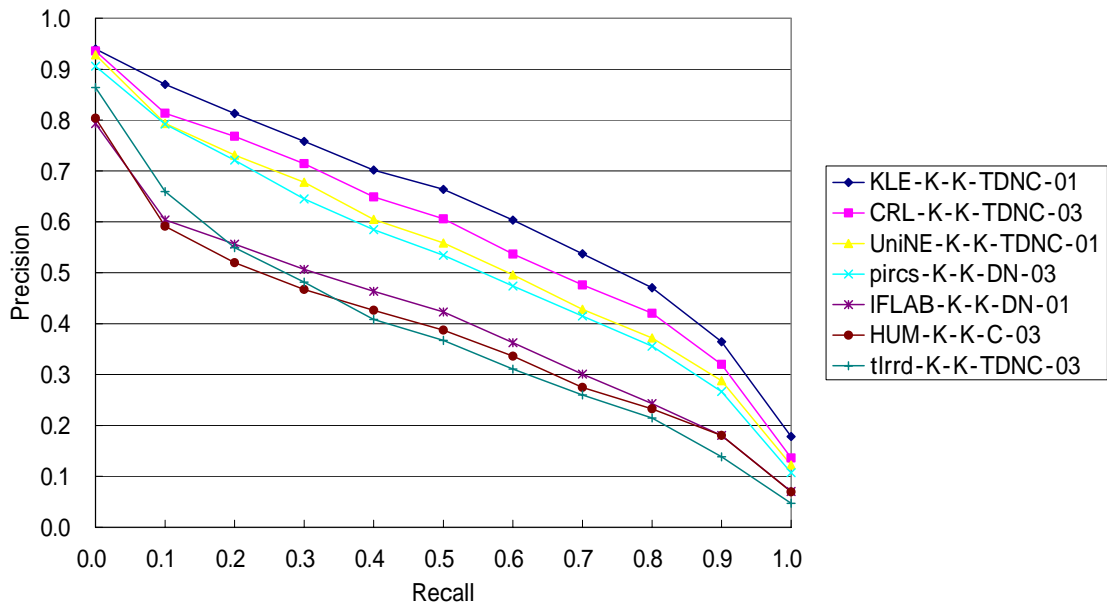
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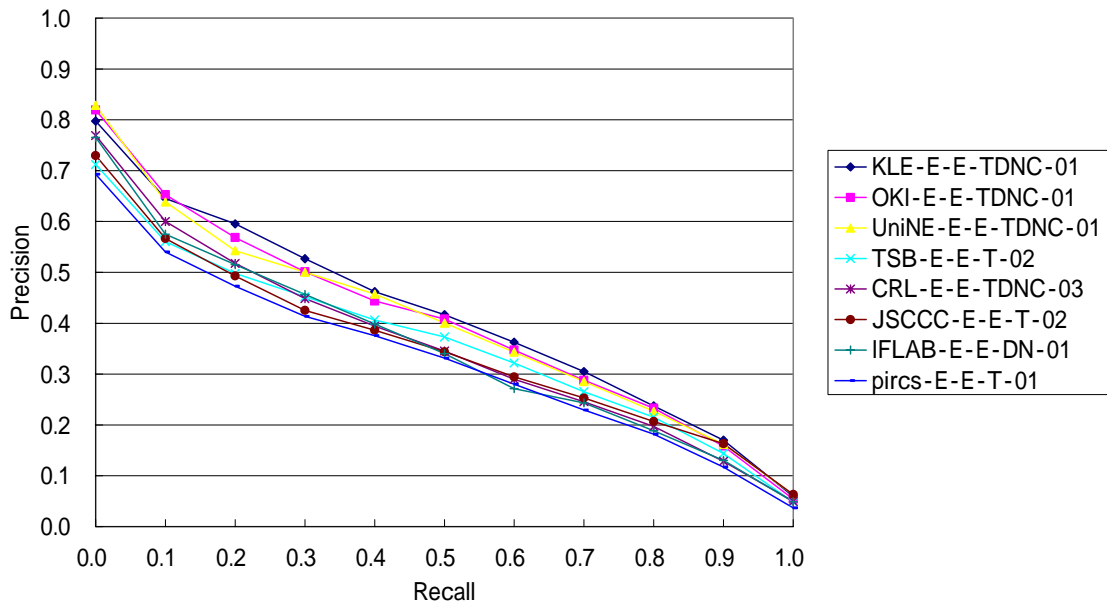
K-K-O(Rigid)



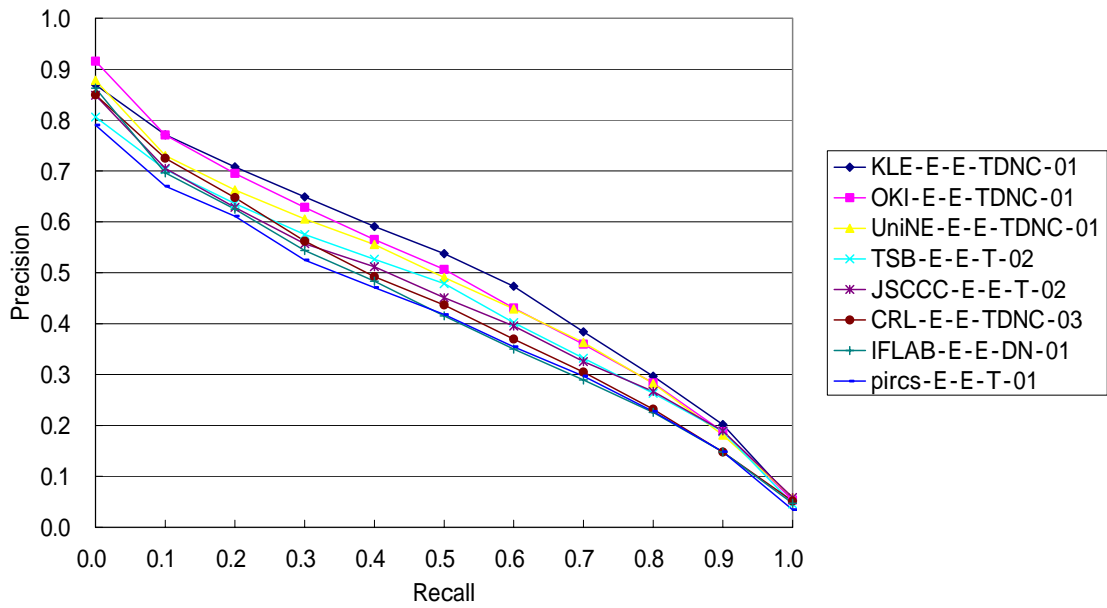
K-K-O(Relax)



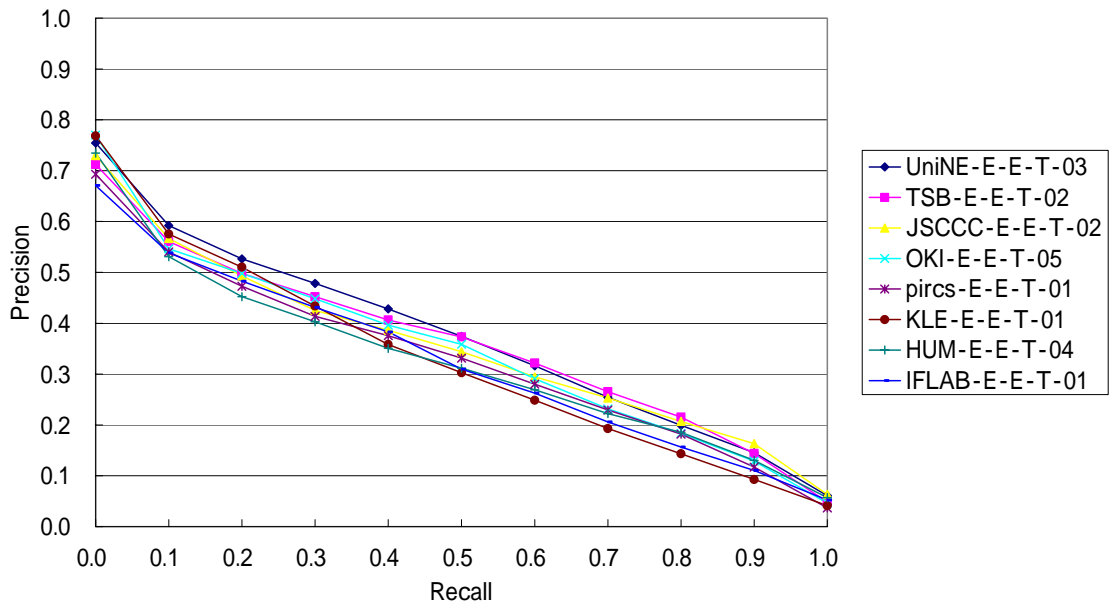
E-E(Rigid)



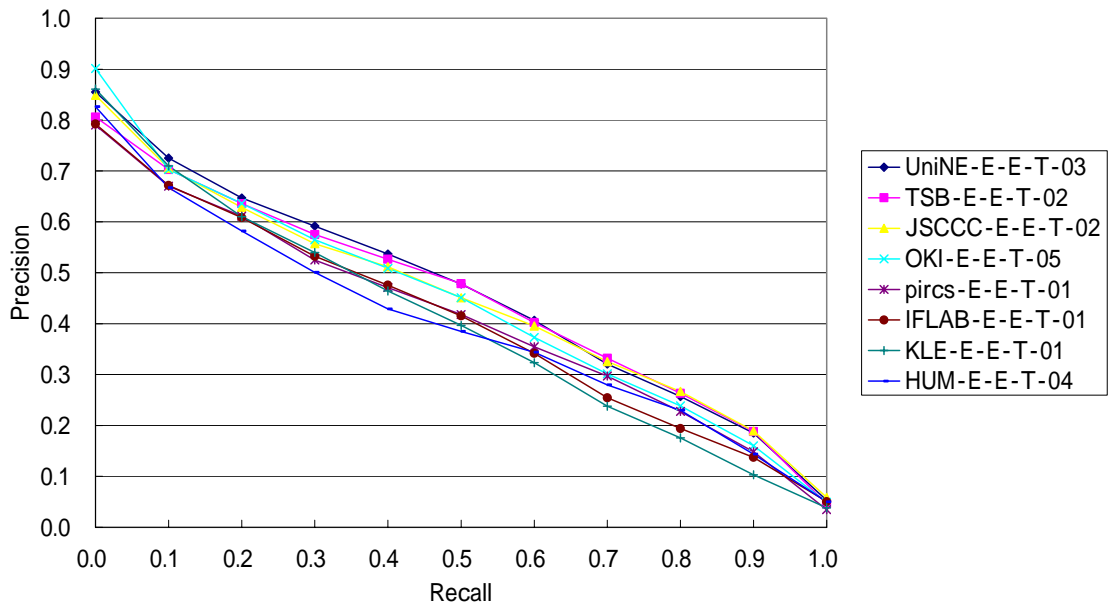
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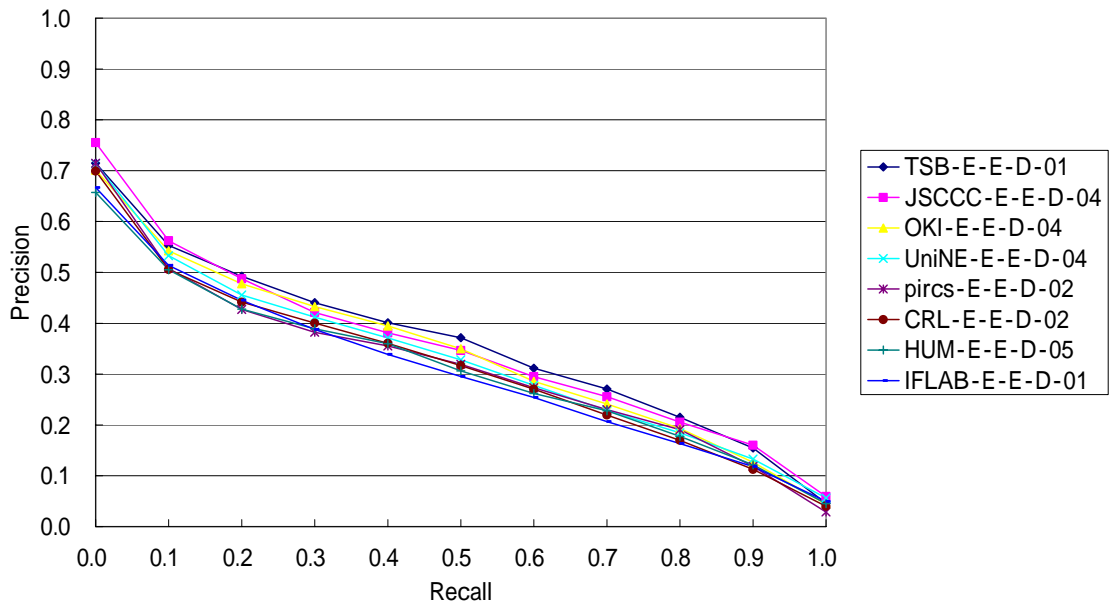
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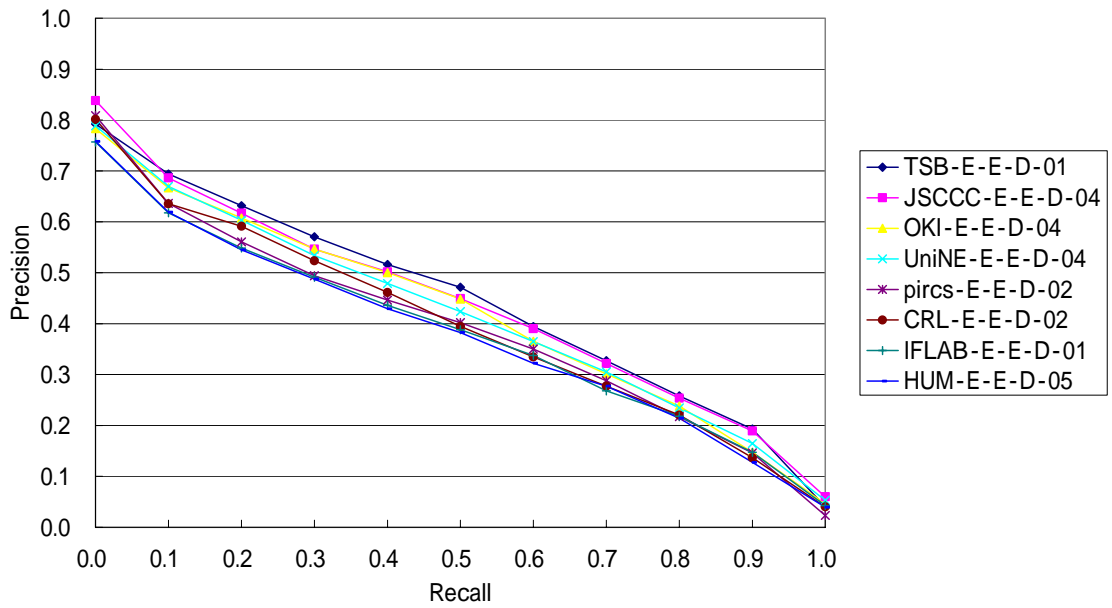
E-E-T(Relax)



E-E-D(Rigid)

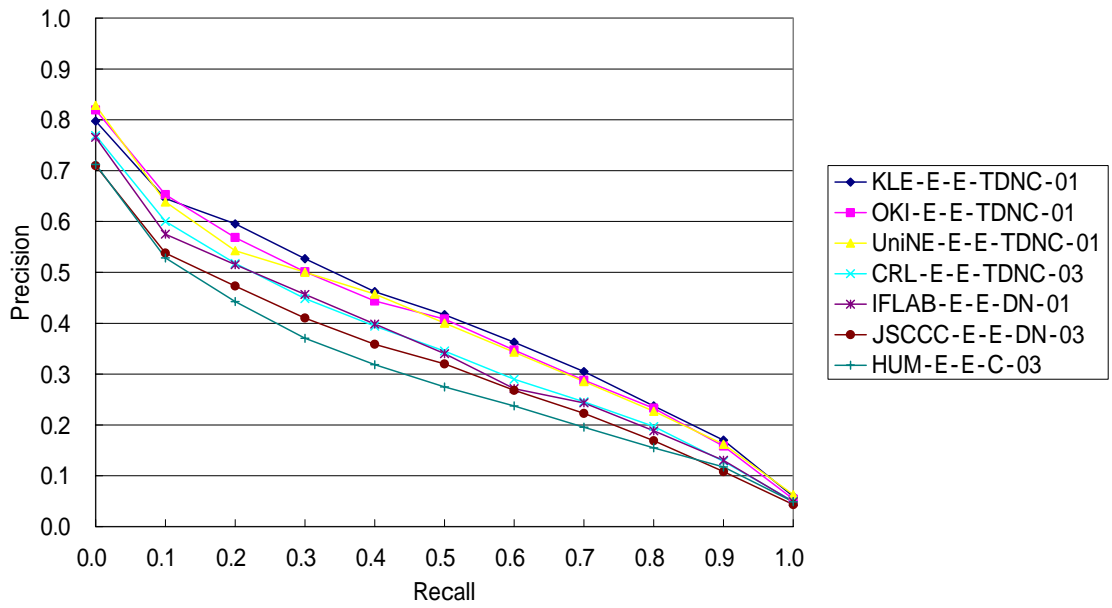


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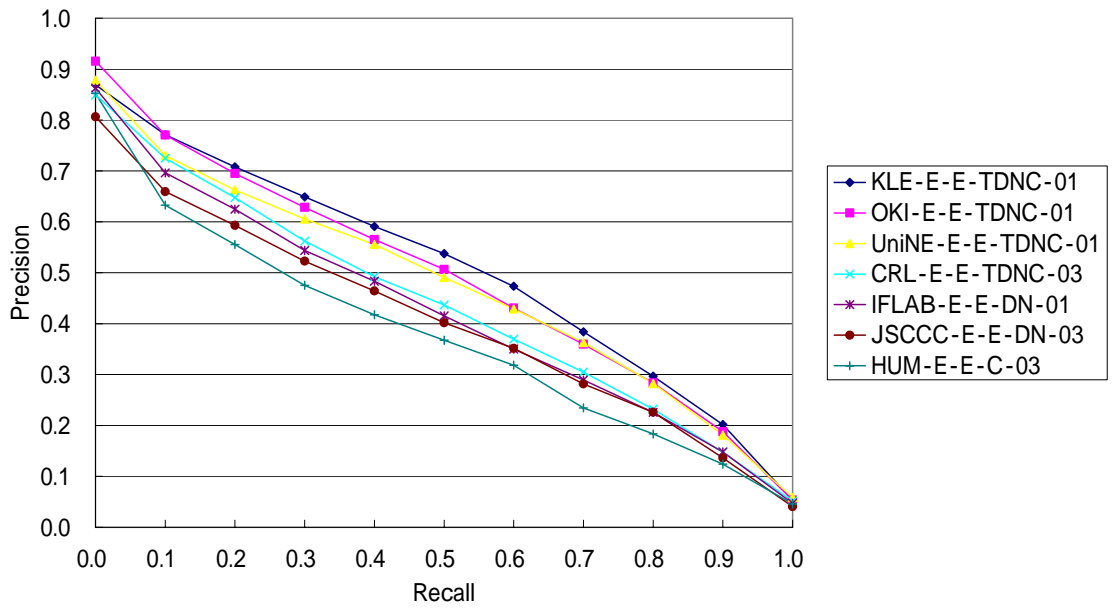




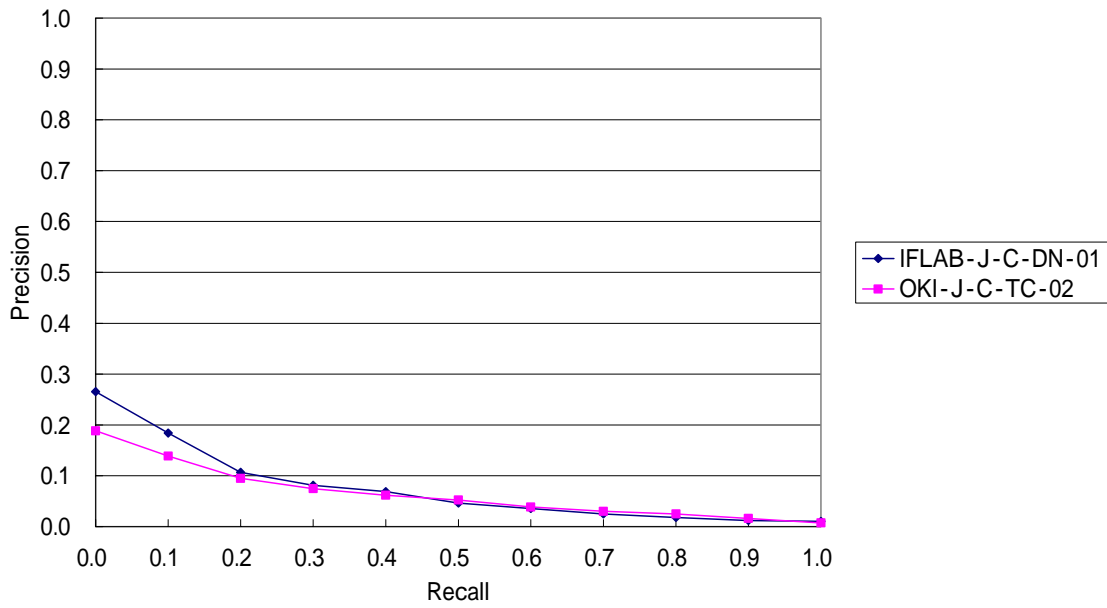
E-E-O(Rigid)



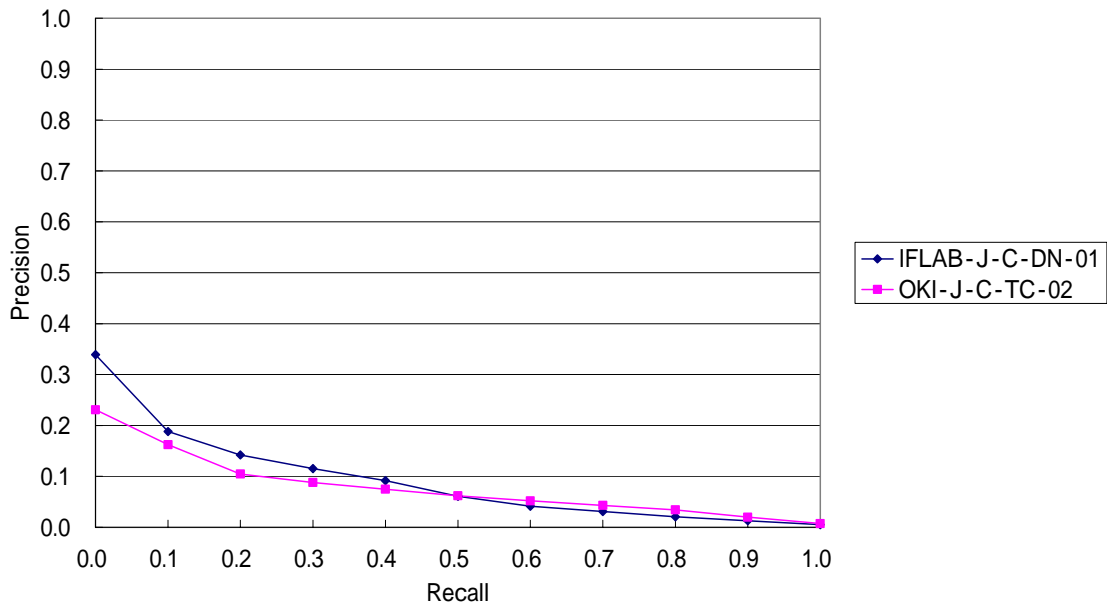
E-E-O(Relax)



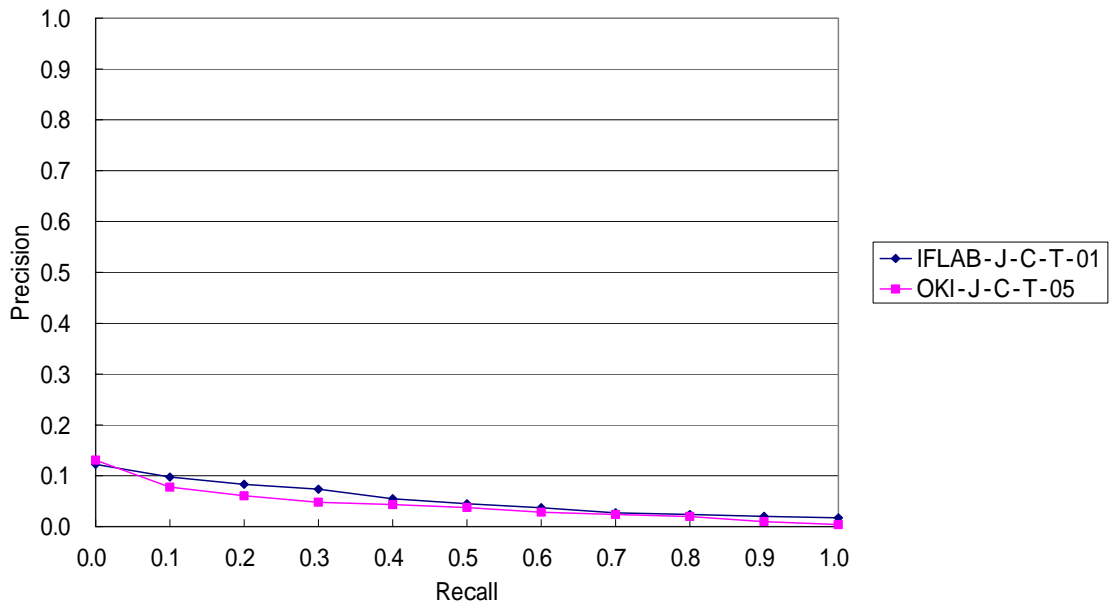
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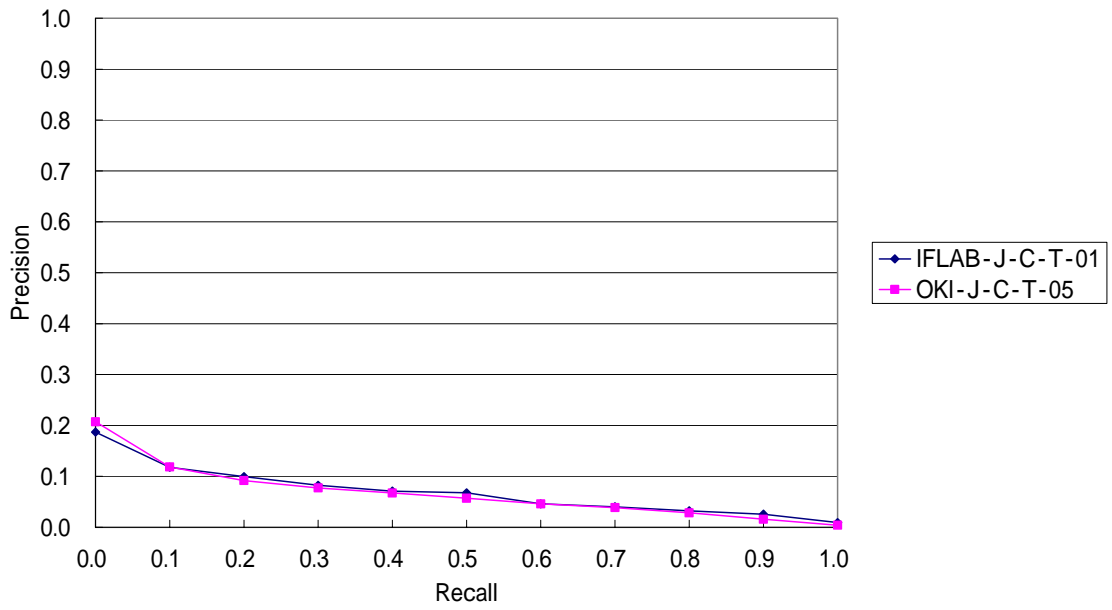
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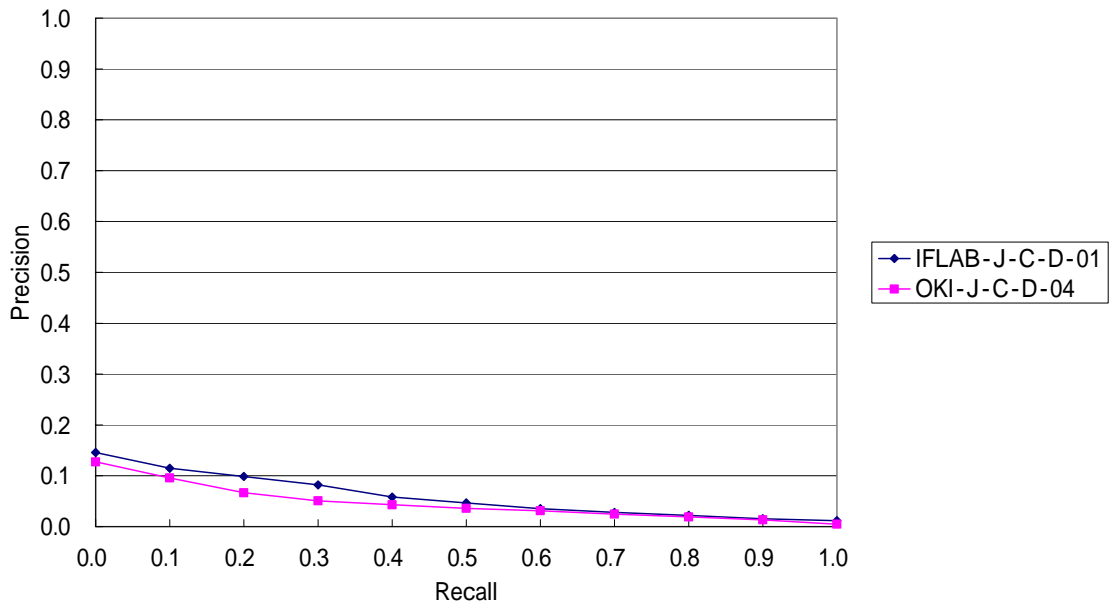
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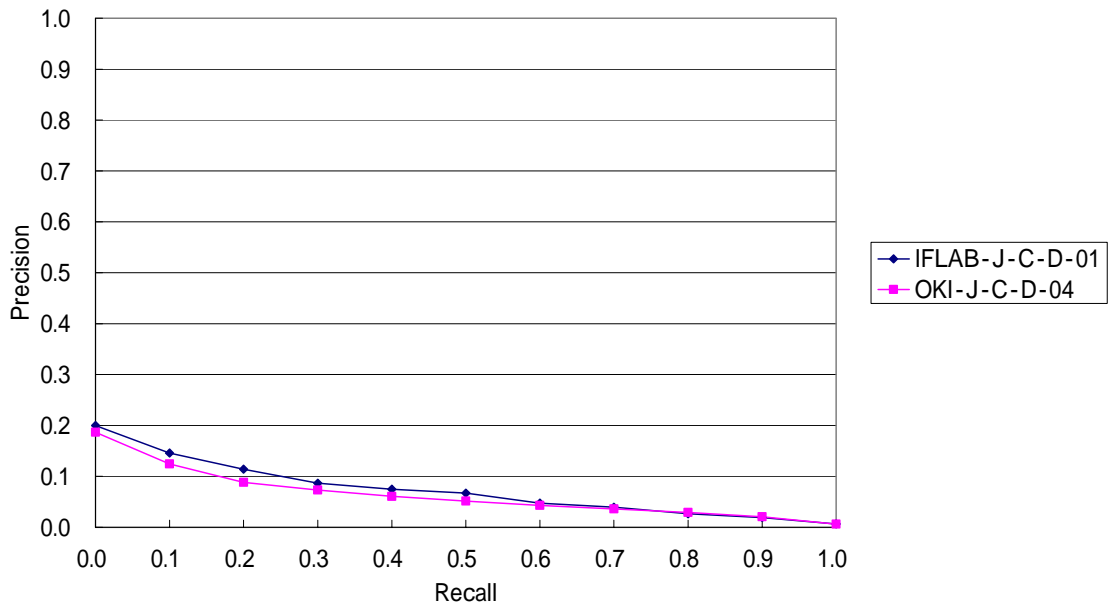
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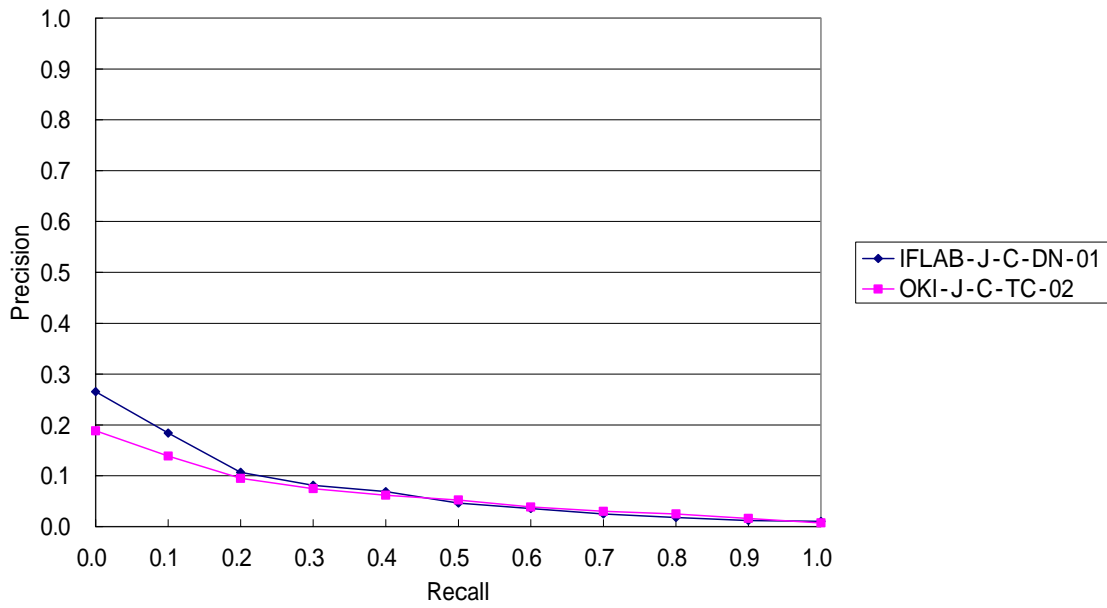
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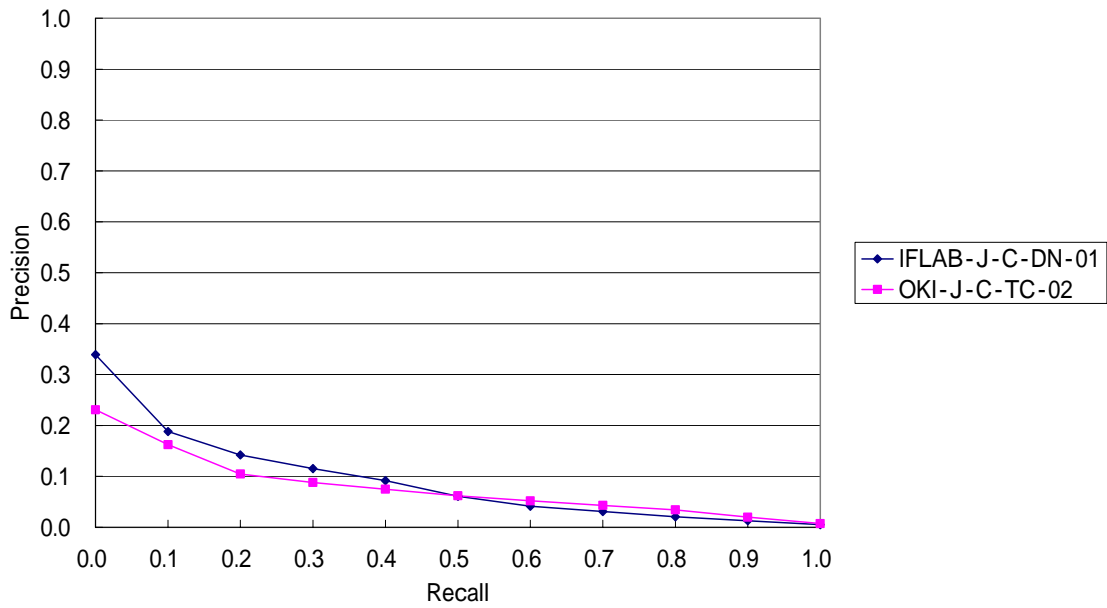
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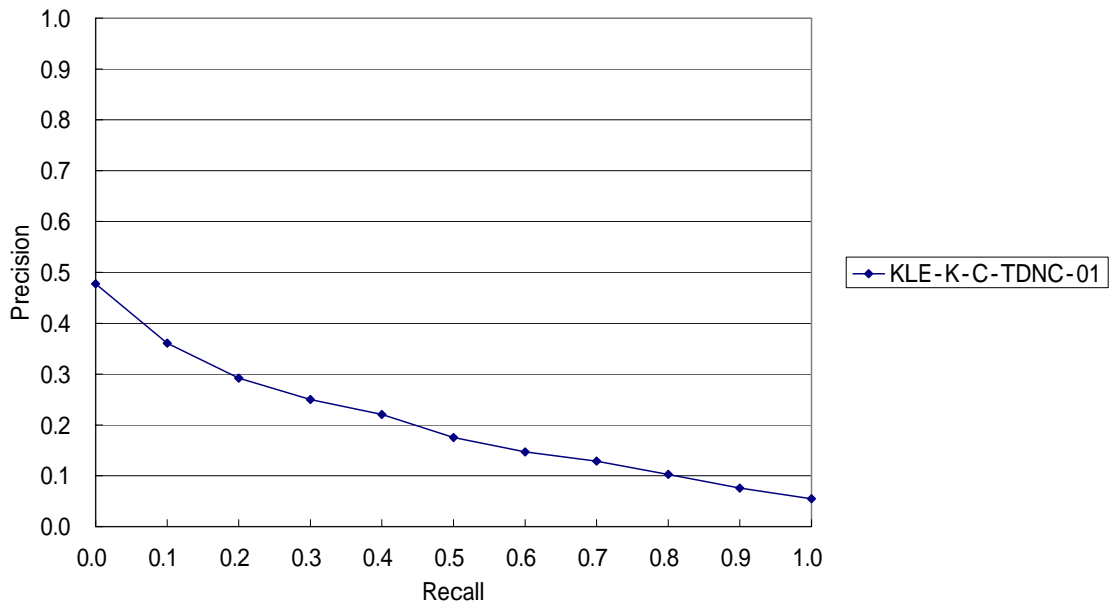
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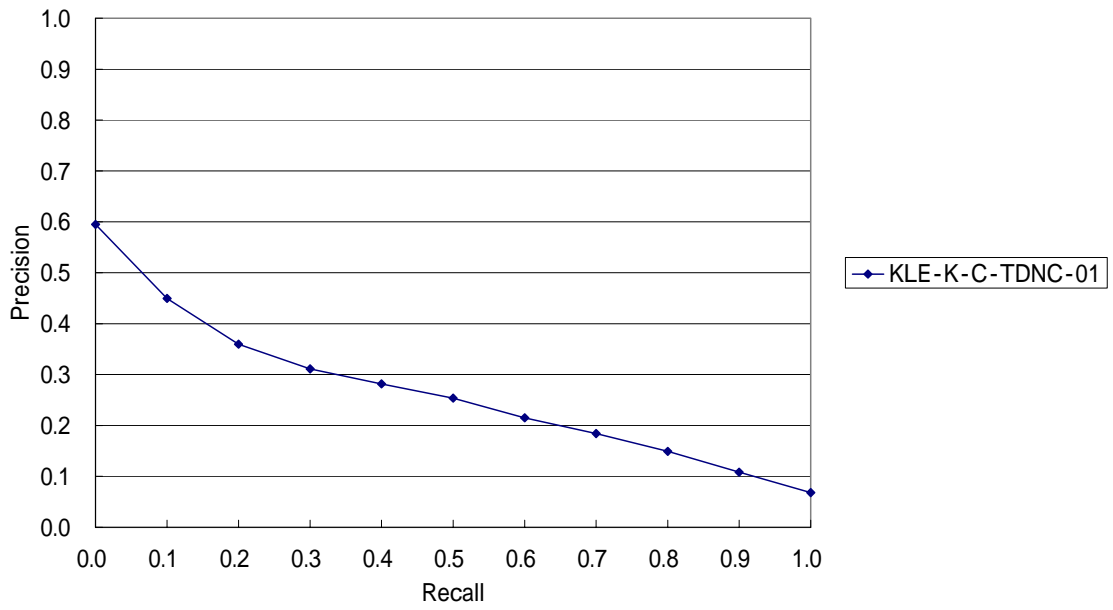
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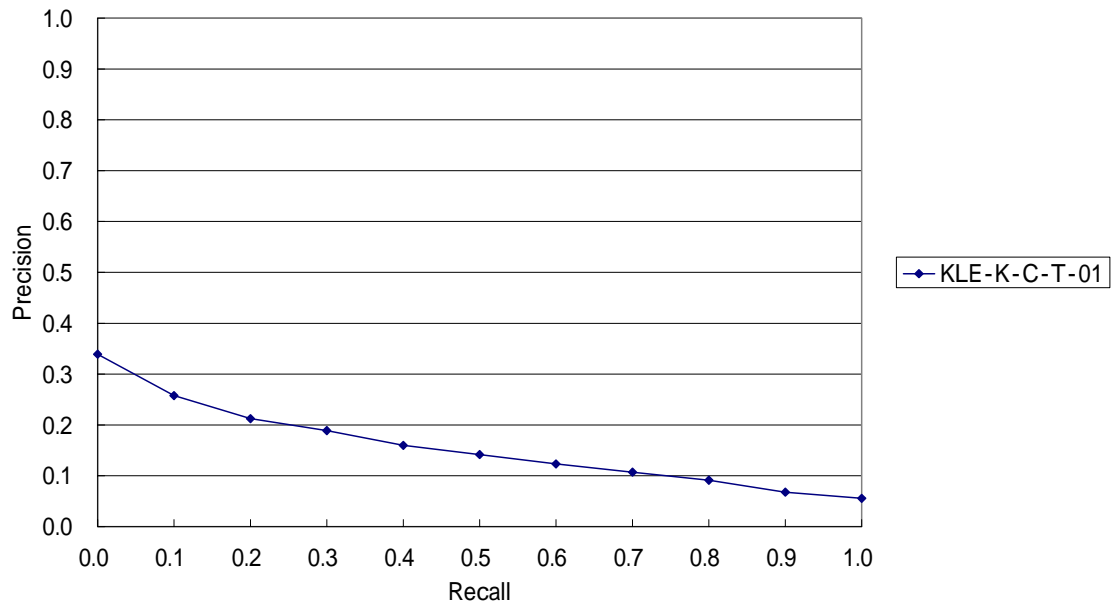
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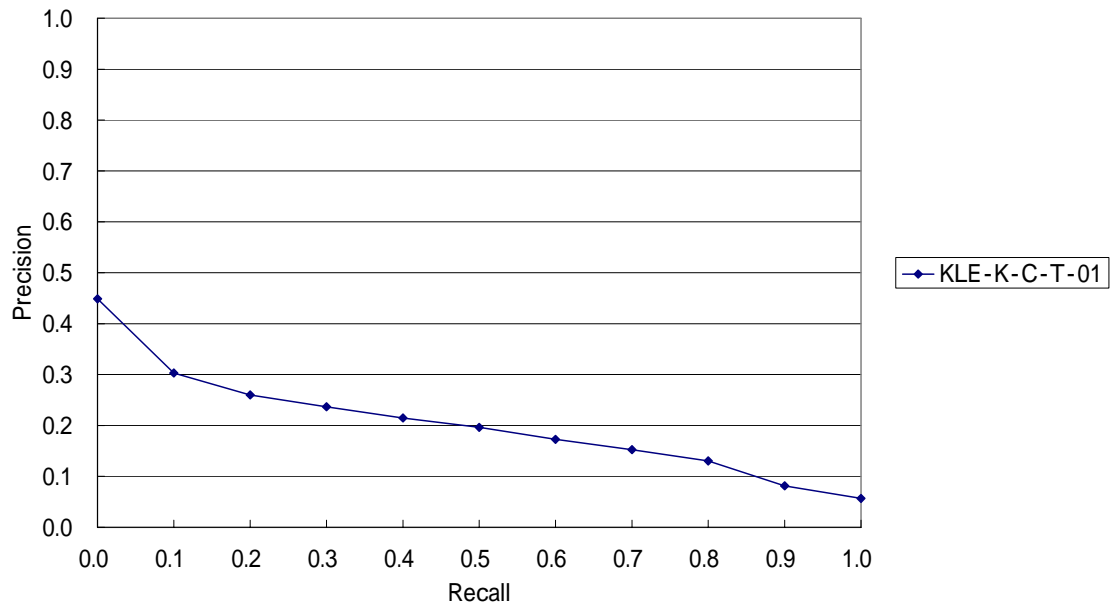
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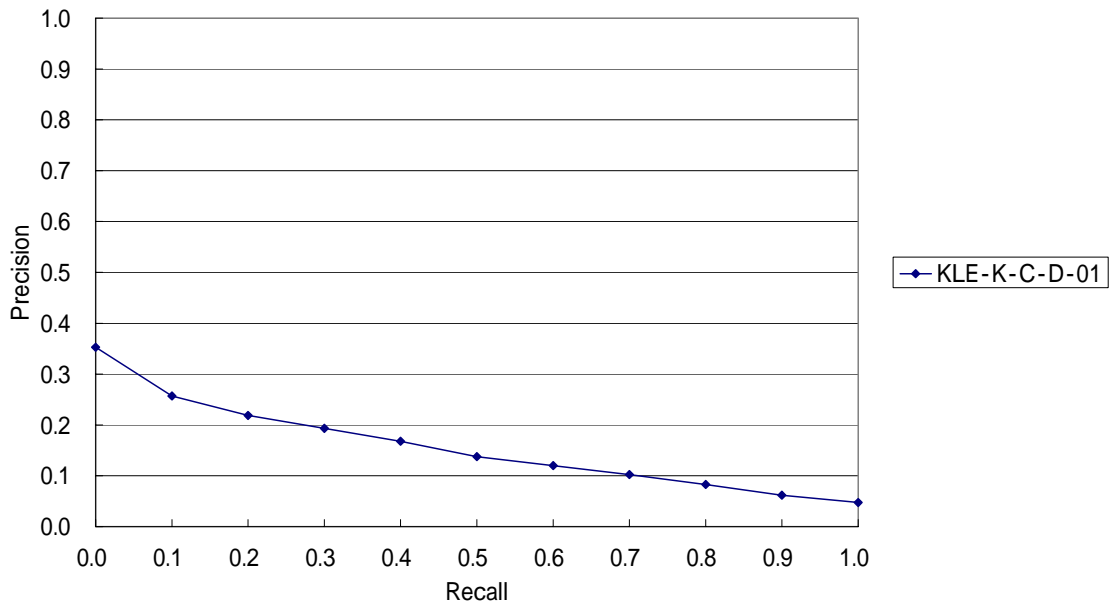
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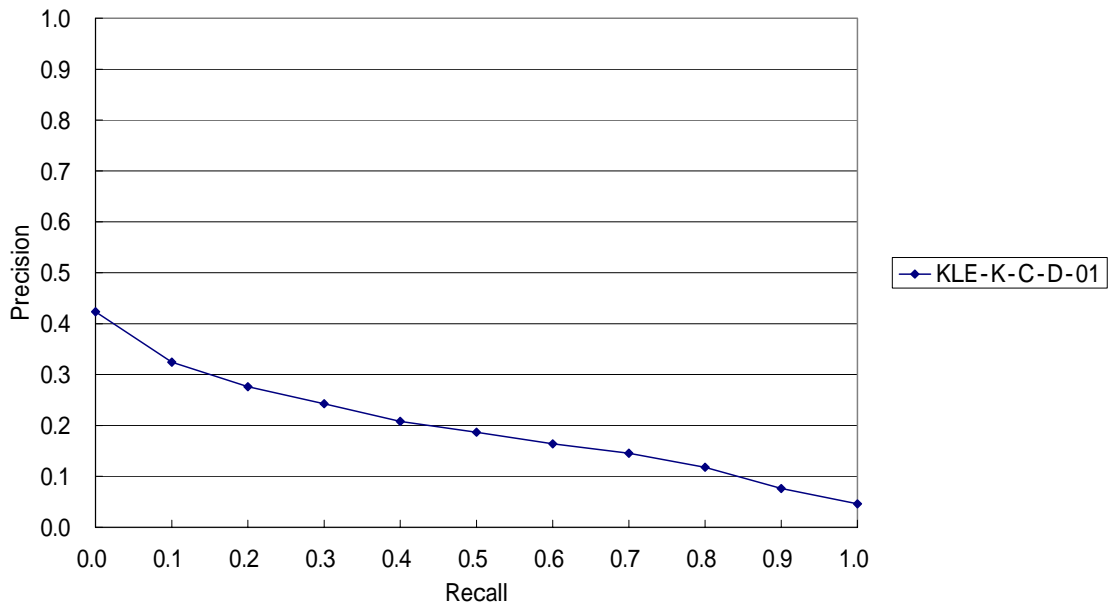
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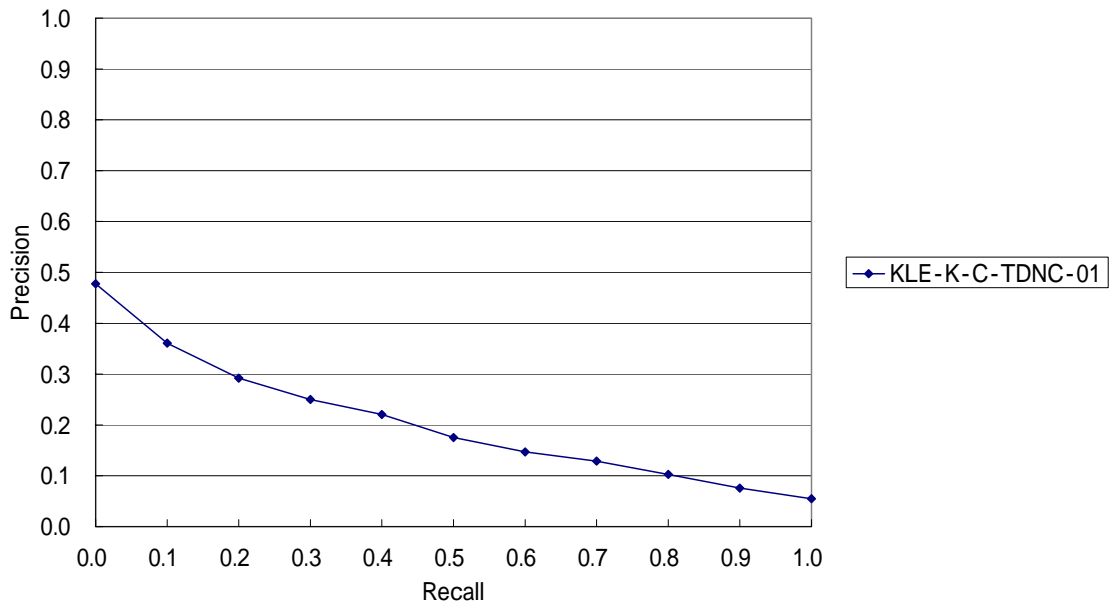


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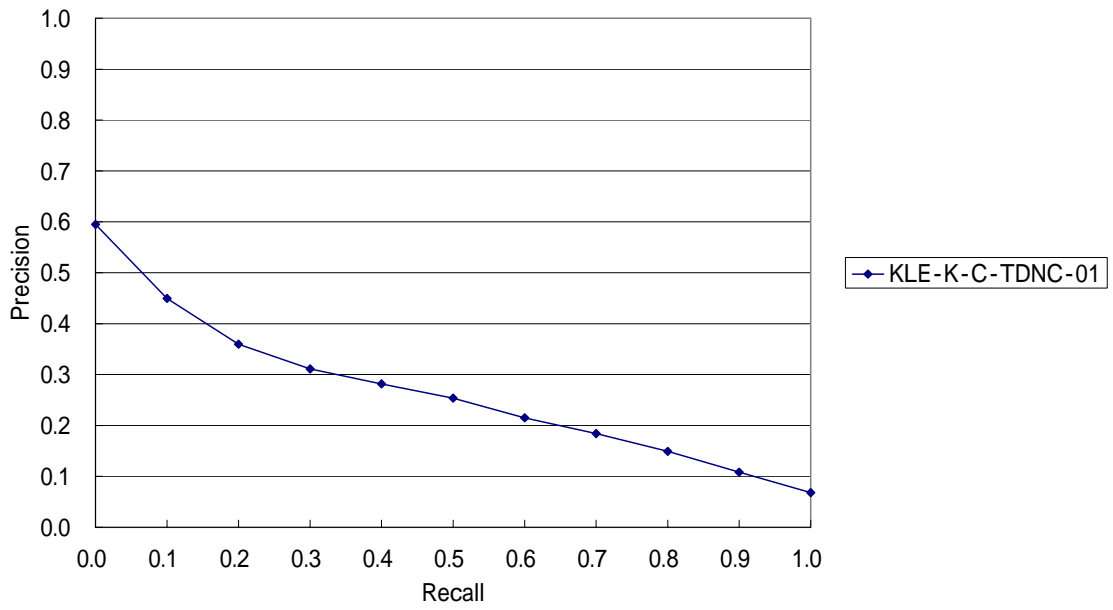




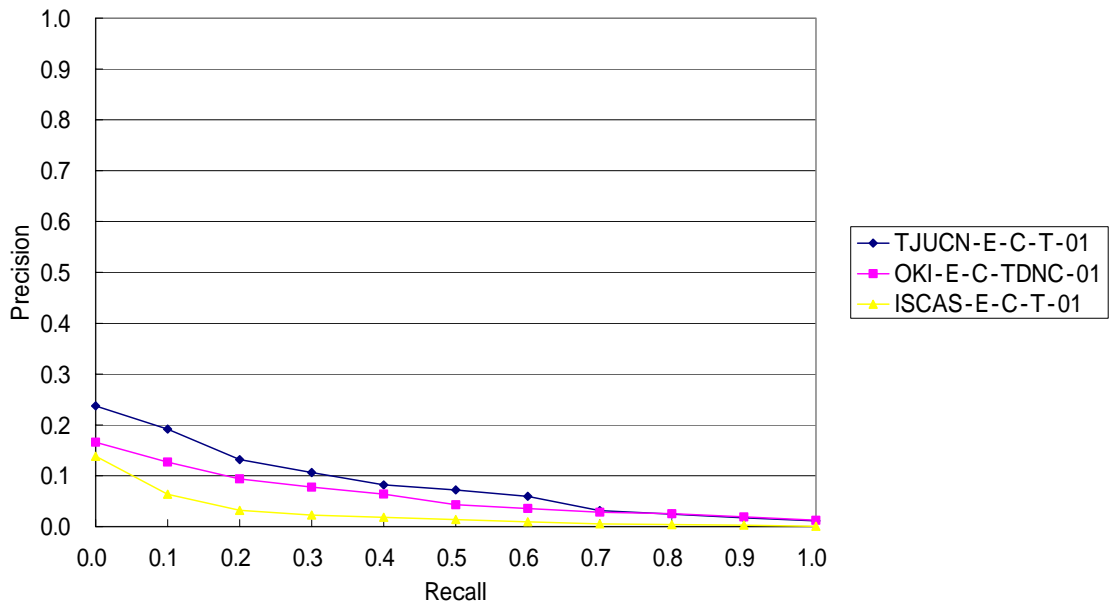
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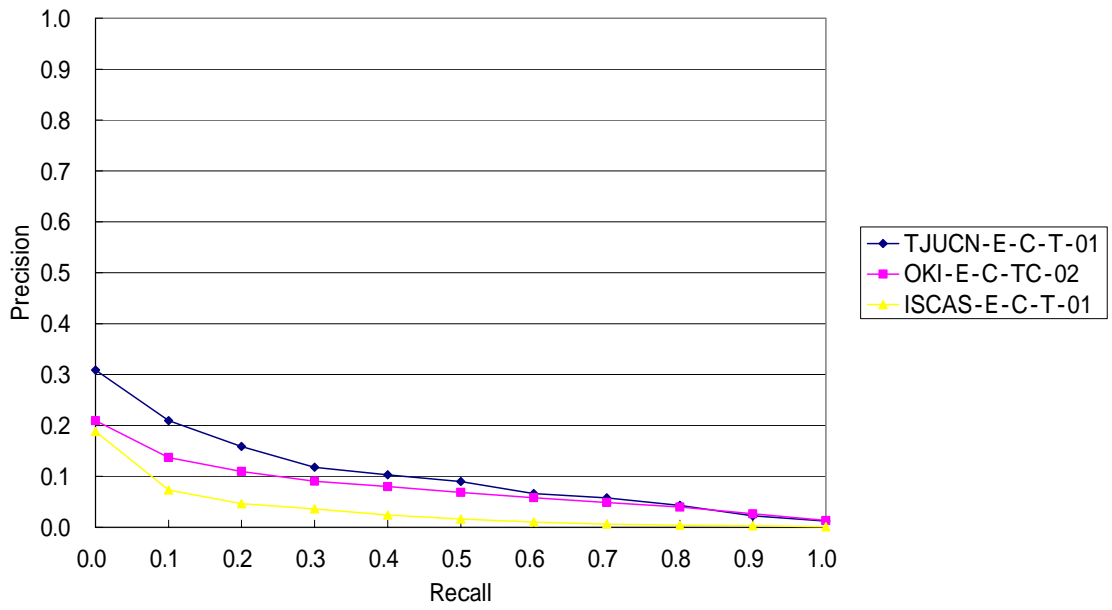
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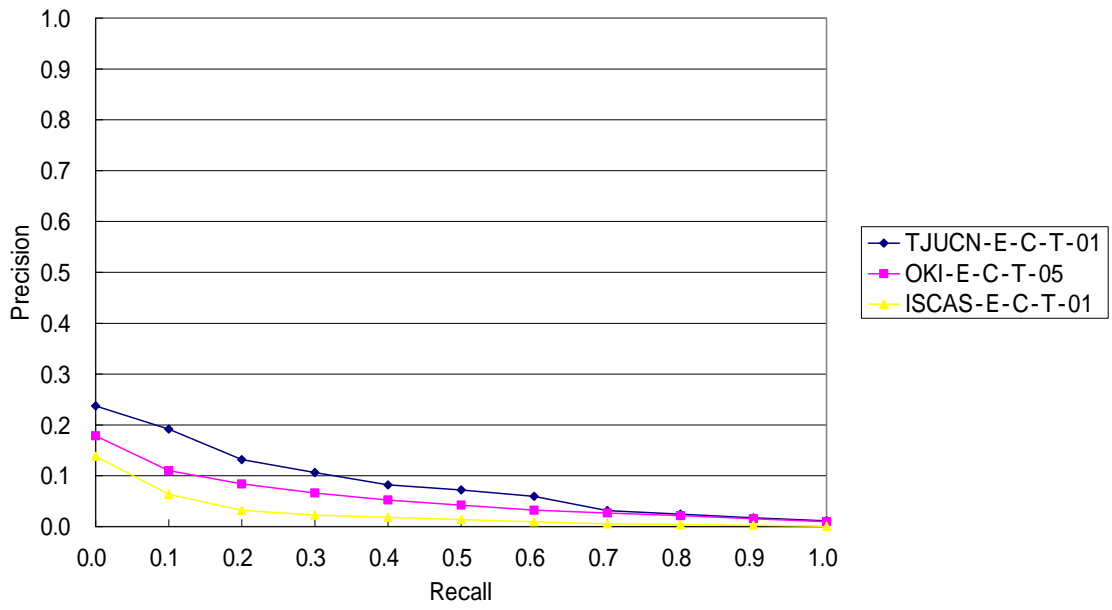
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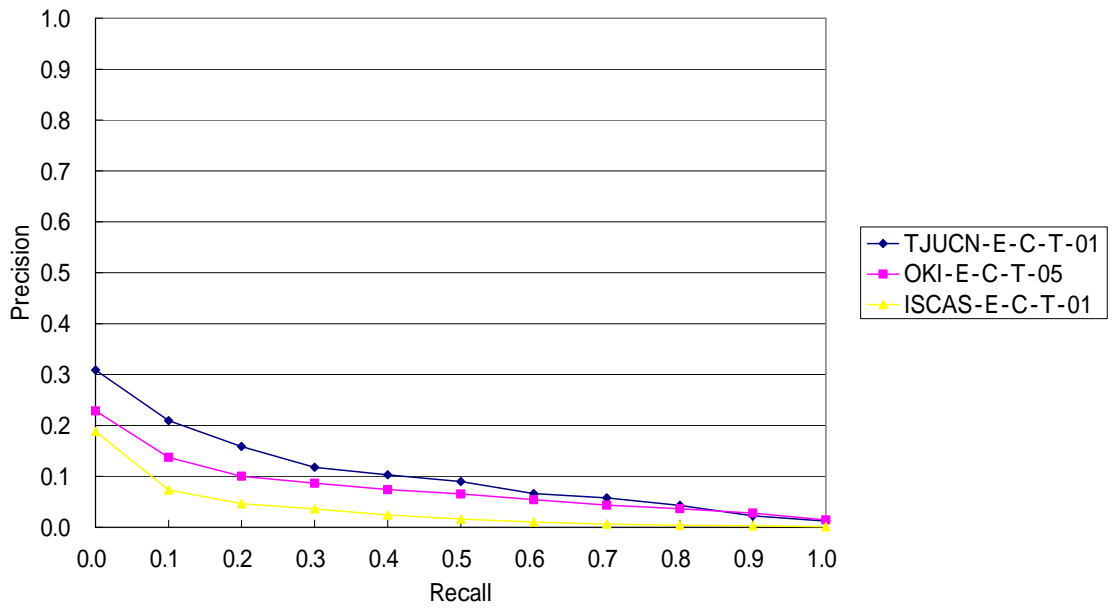
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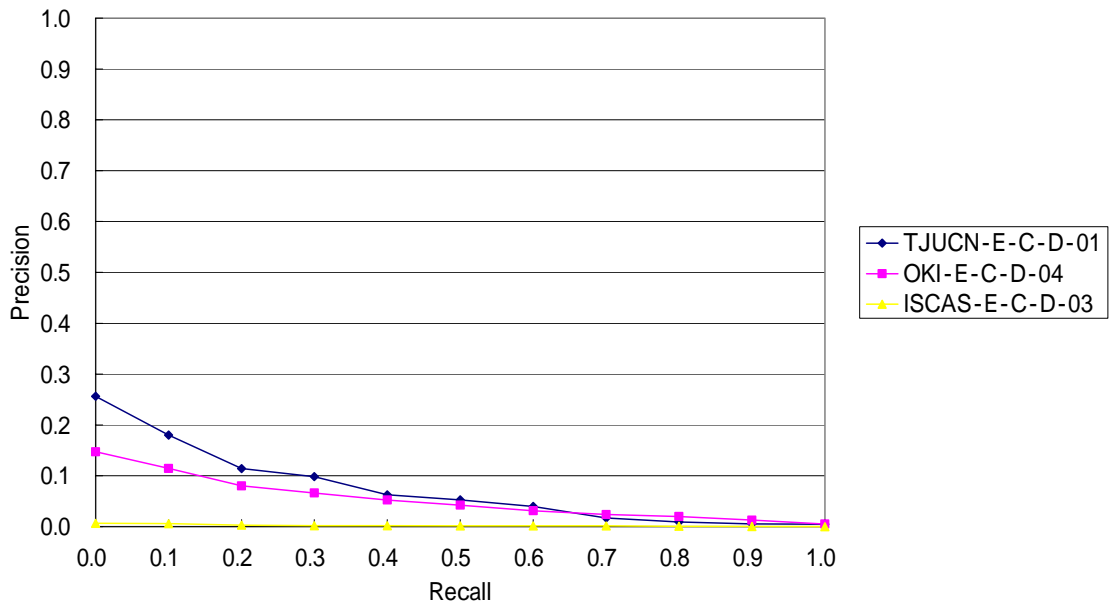
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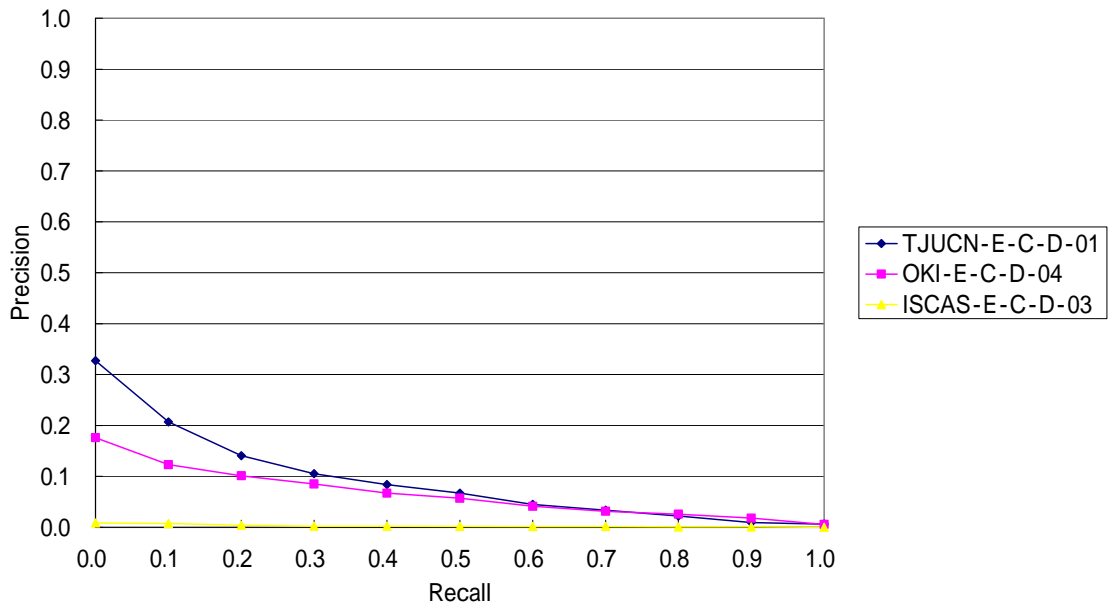
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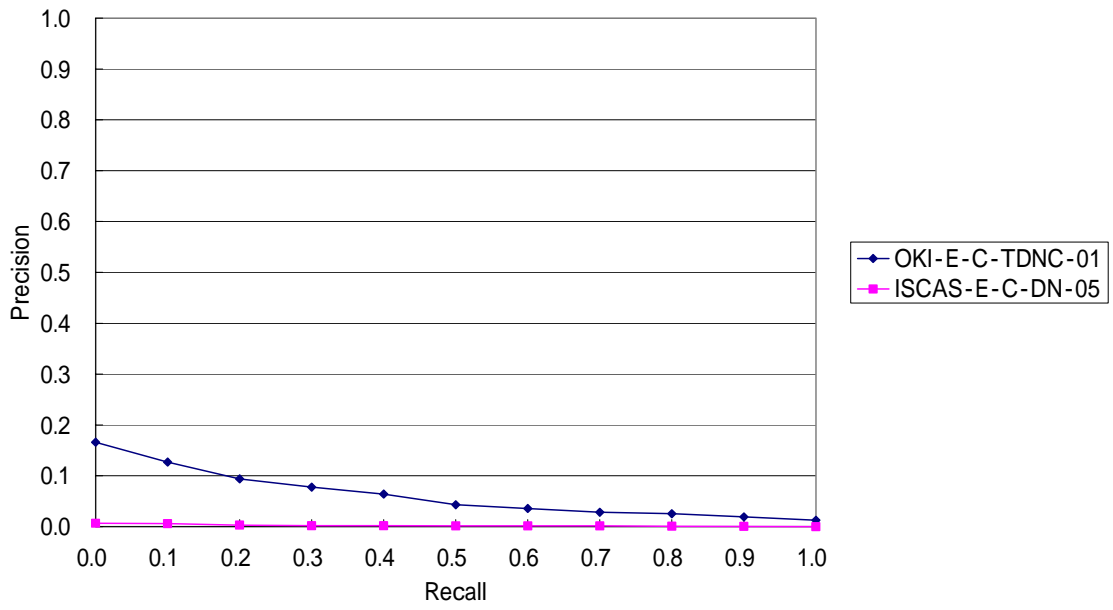
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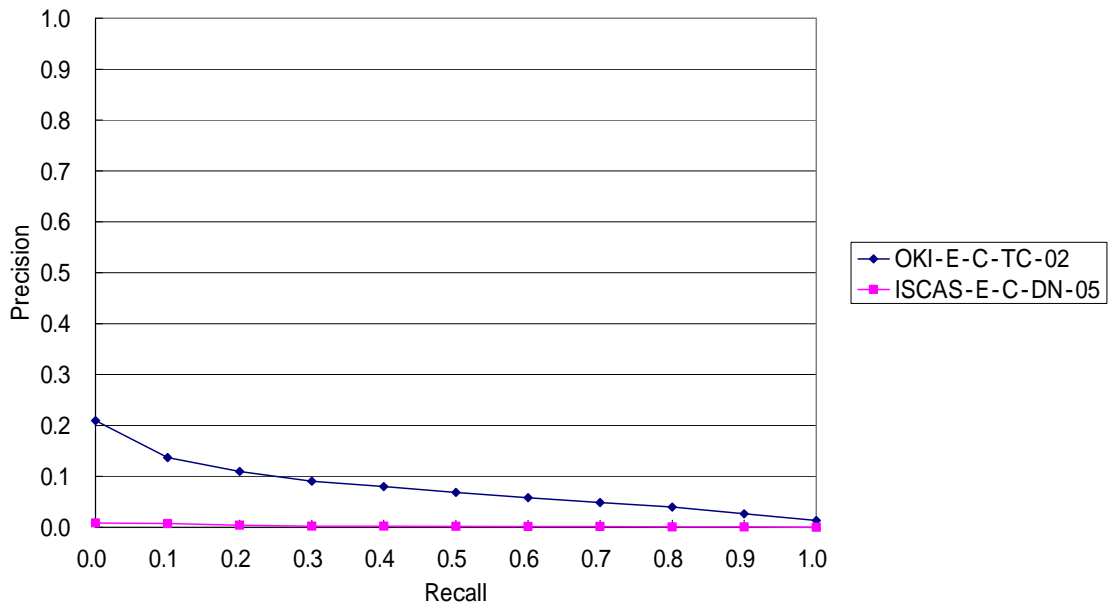
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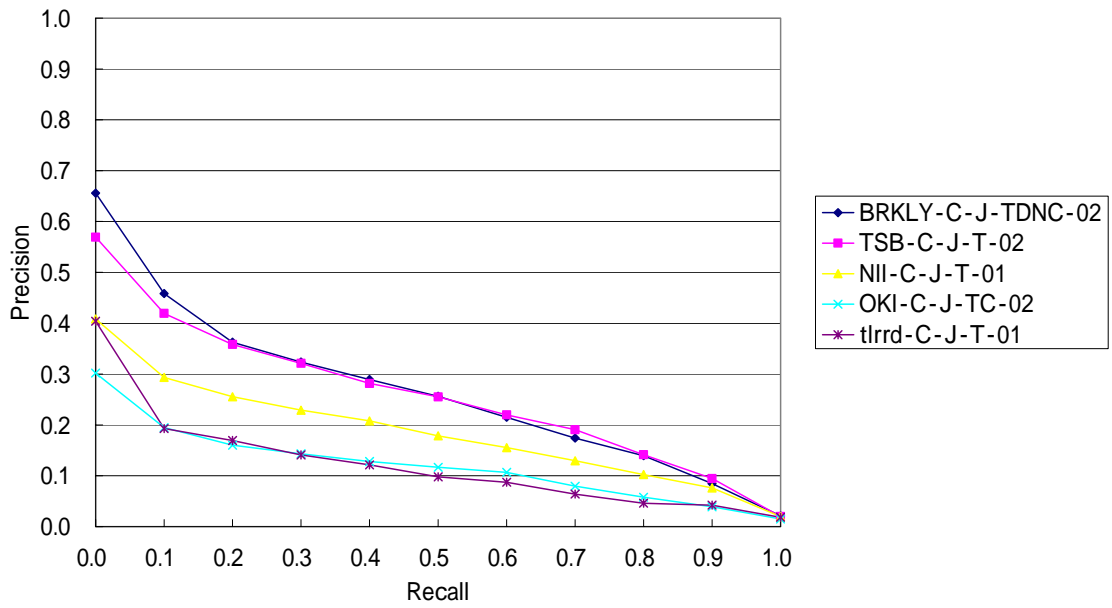
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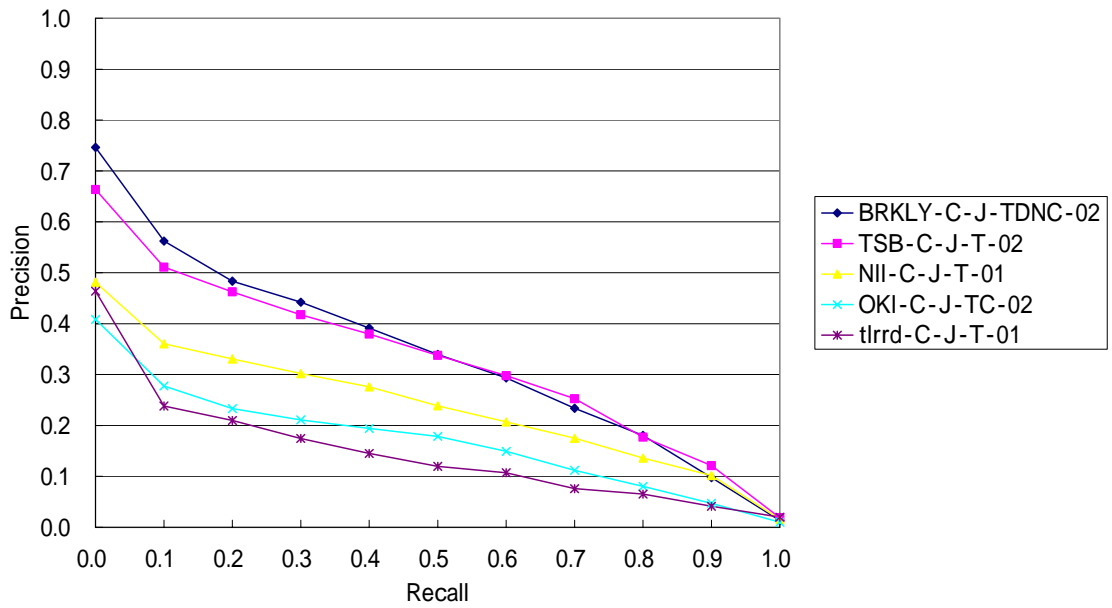
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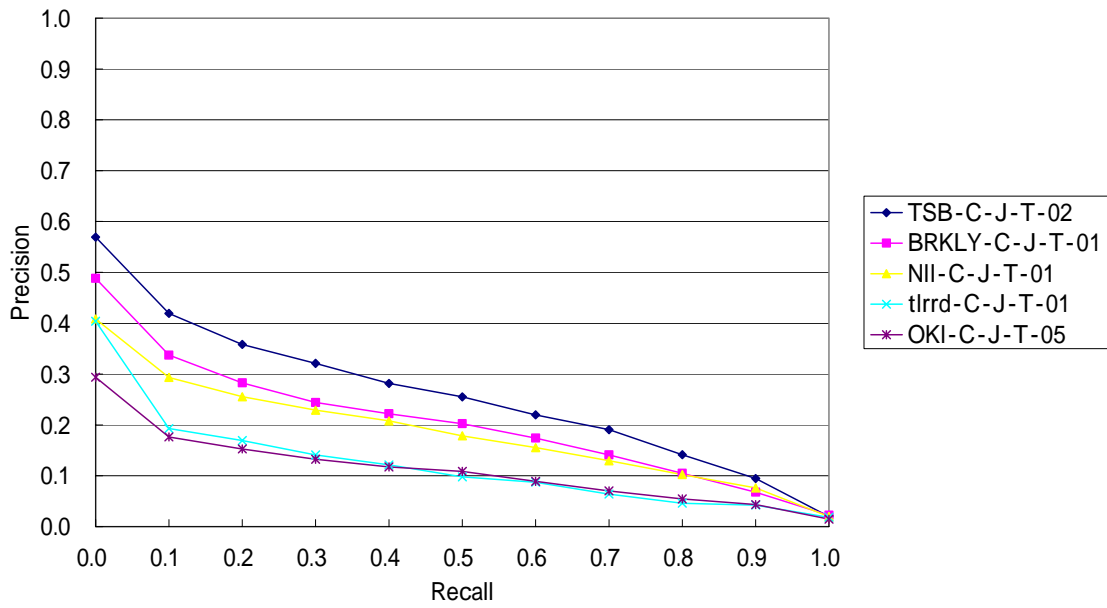
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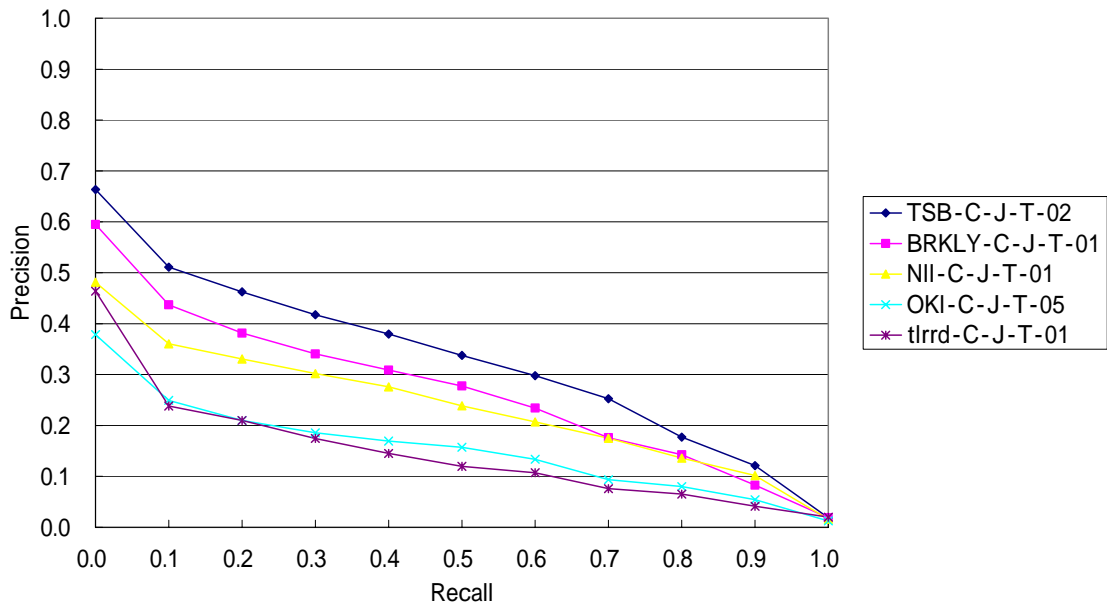
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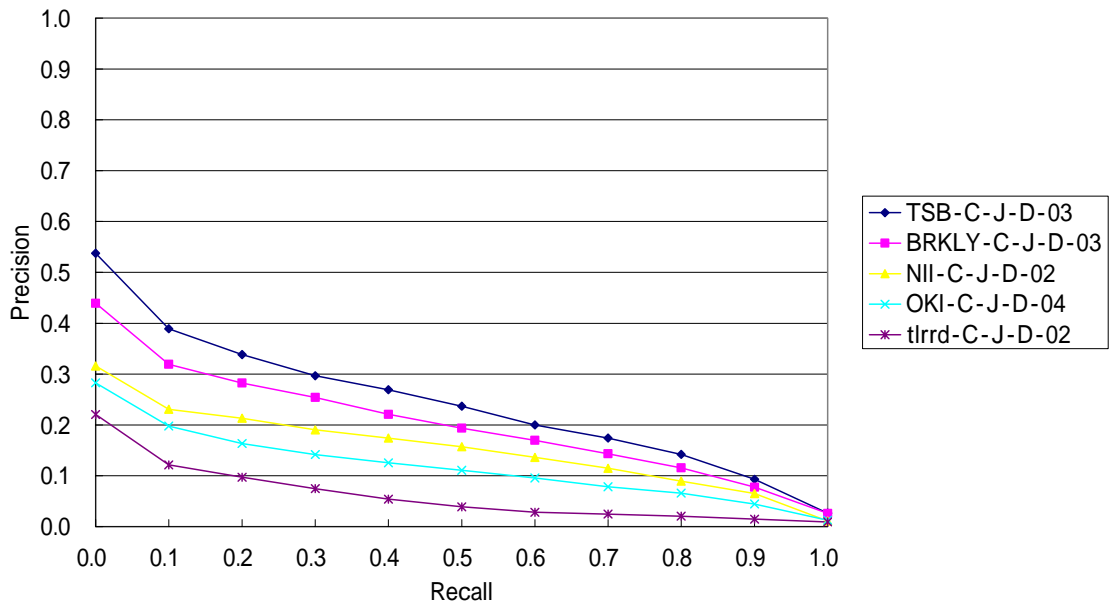
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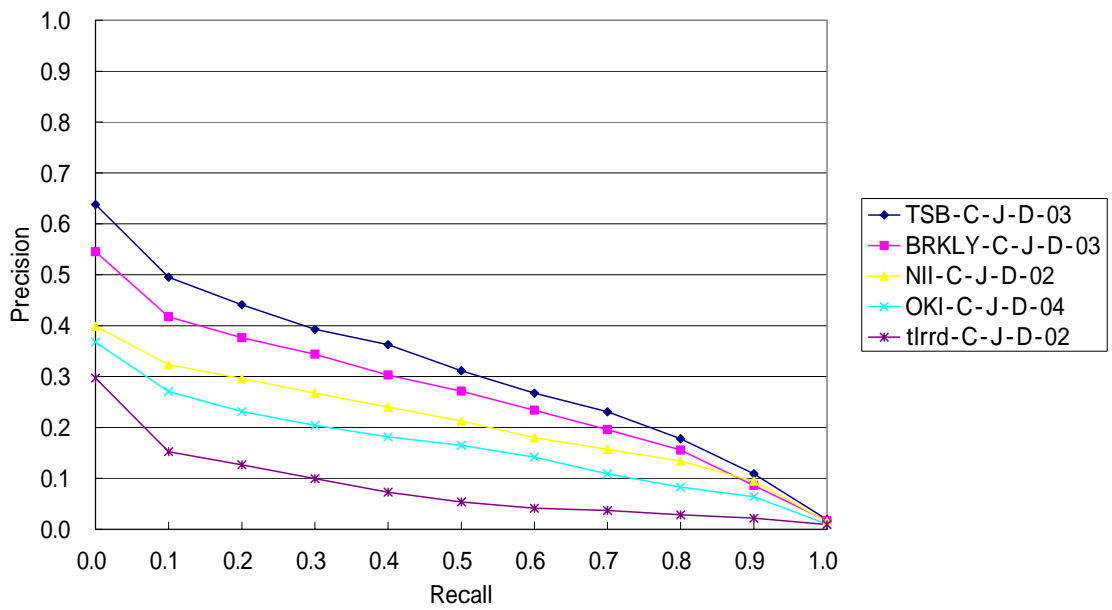
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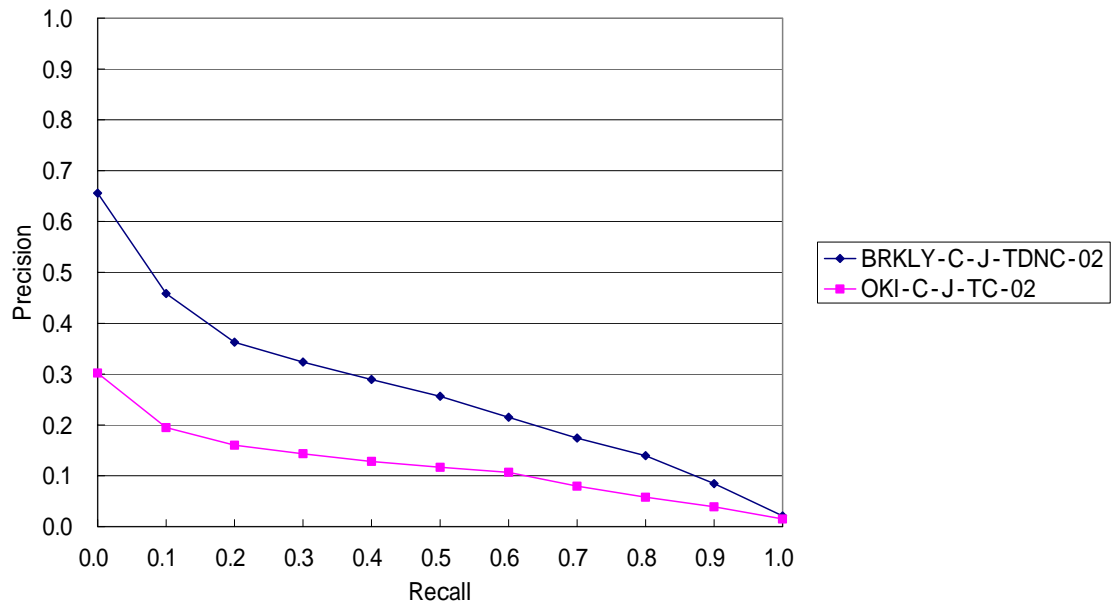


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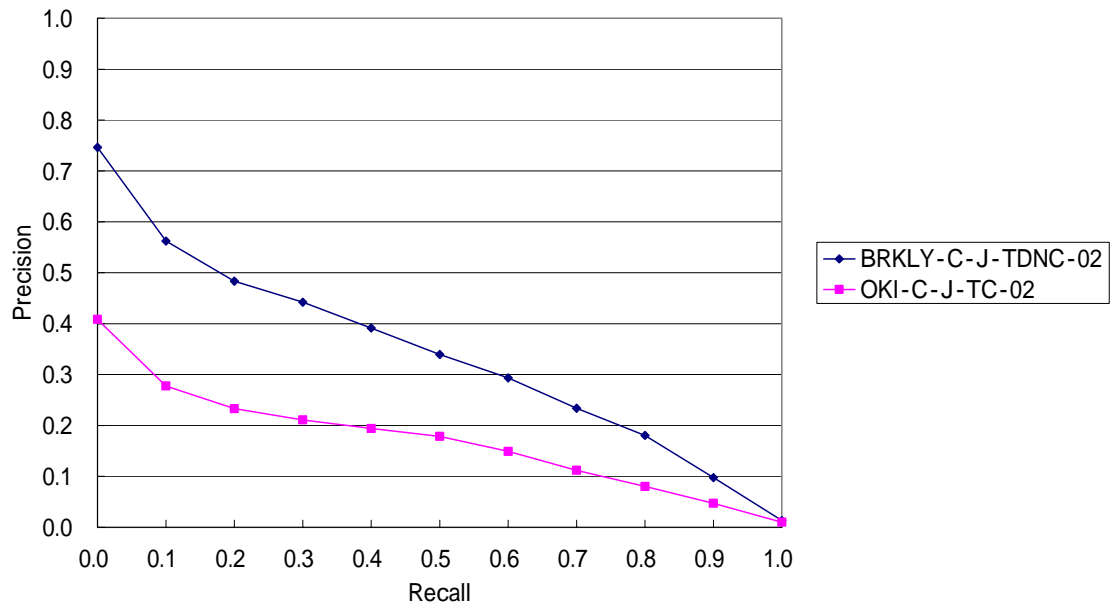




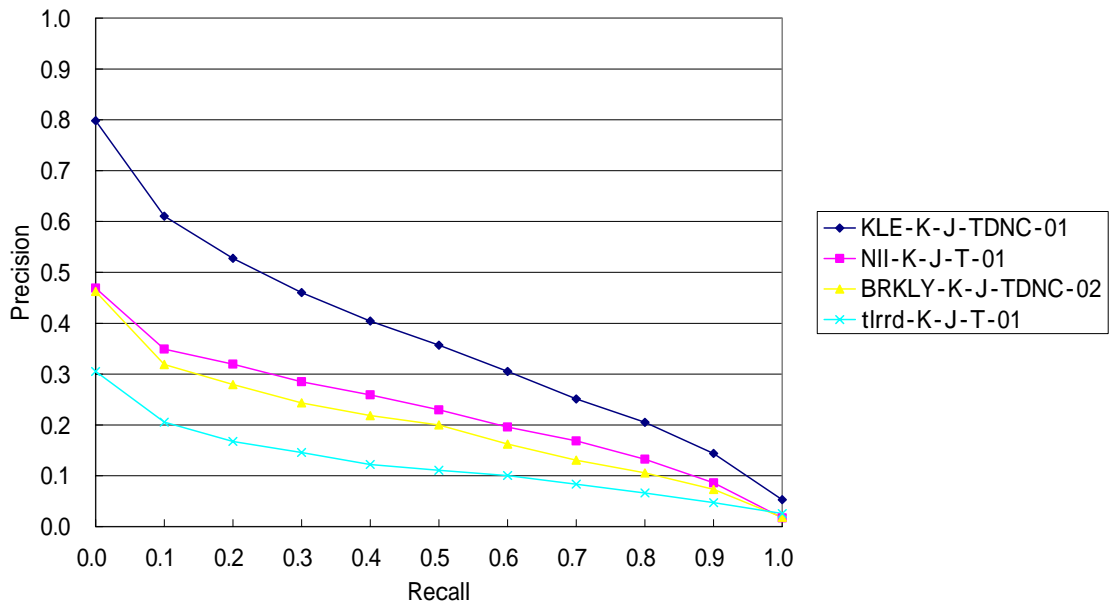
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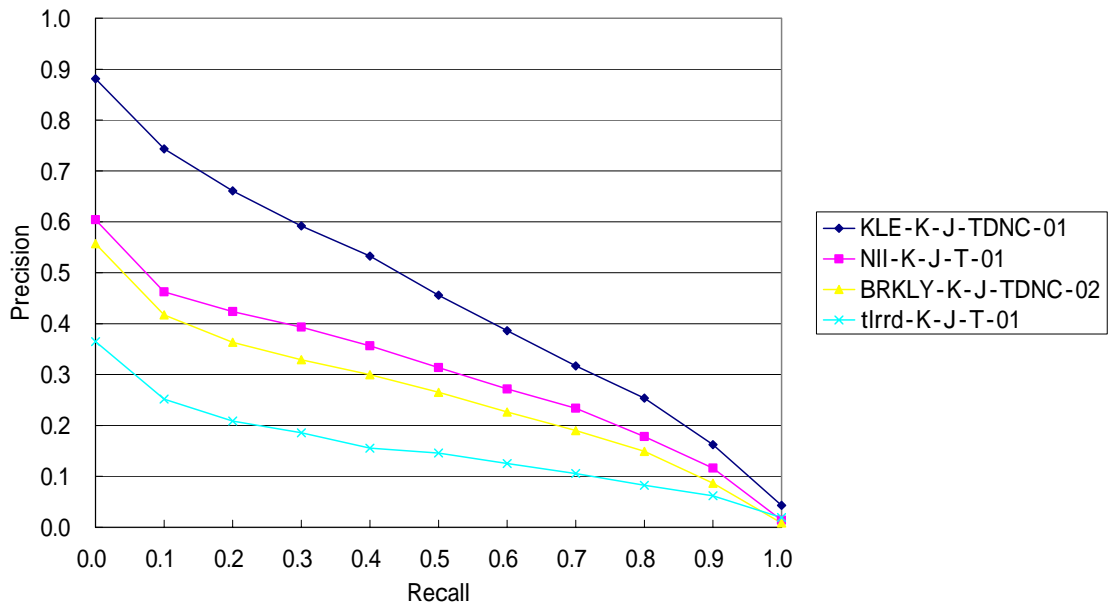
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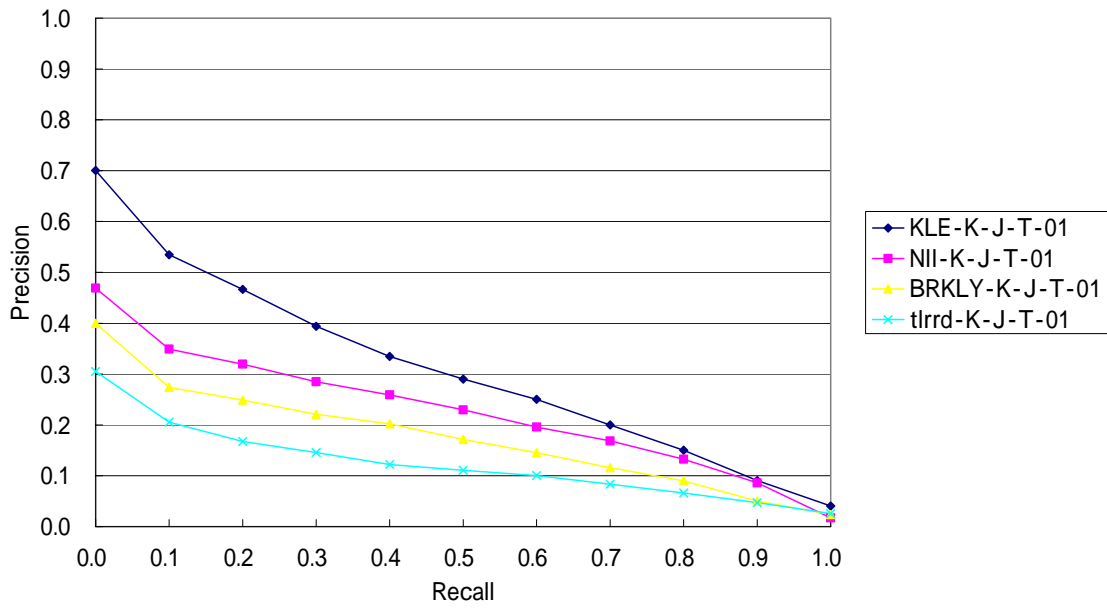
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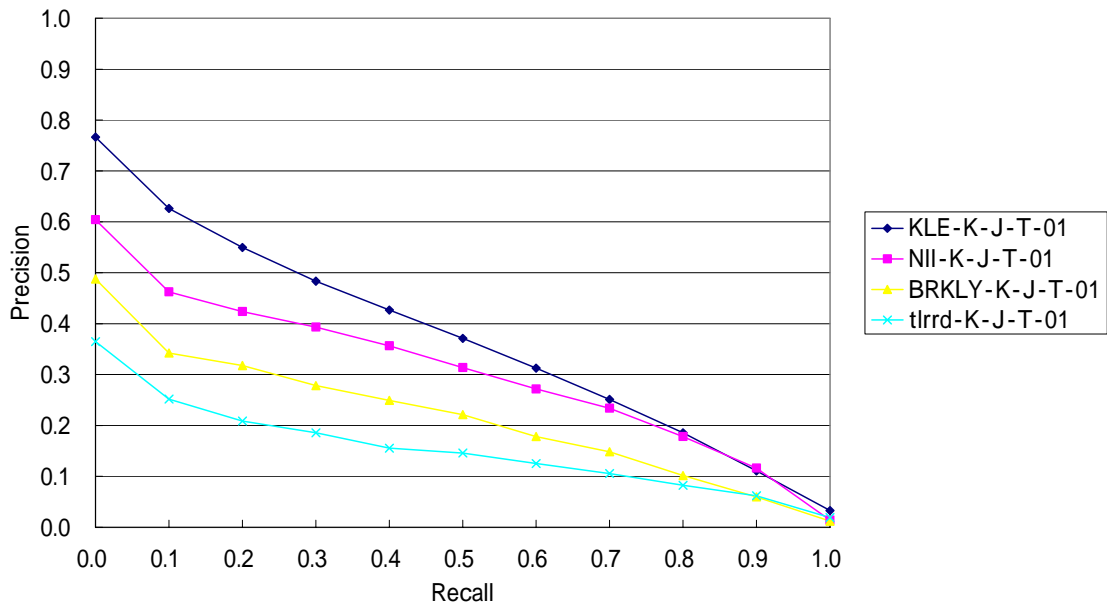
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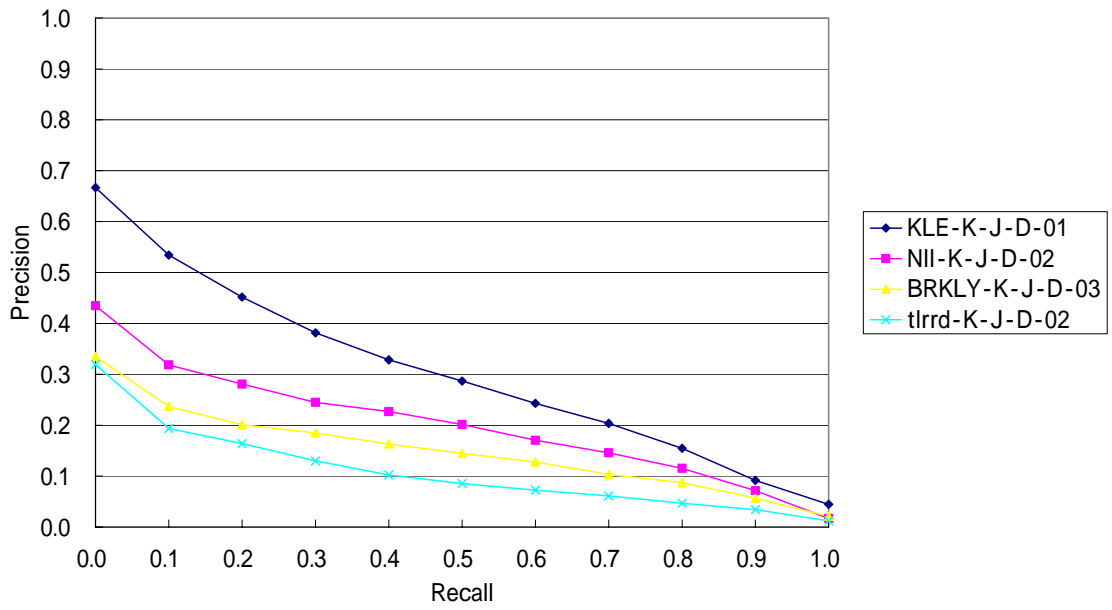
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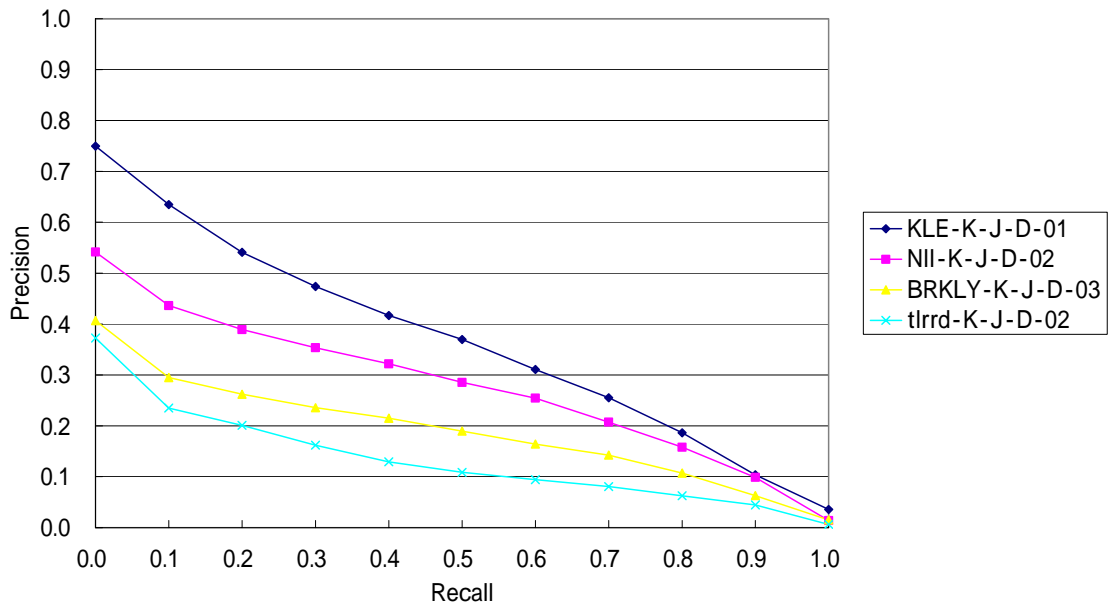
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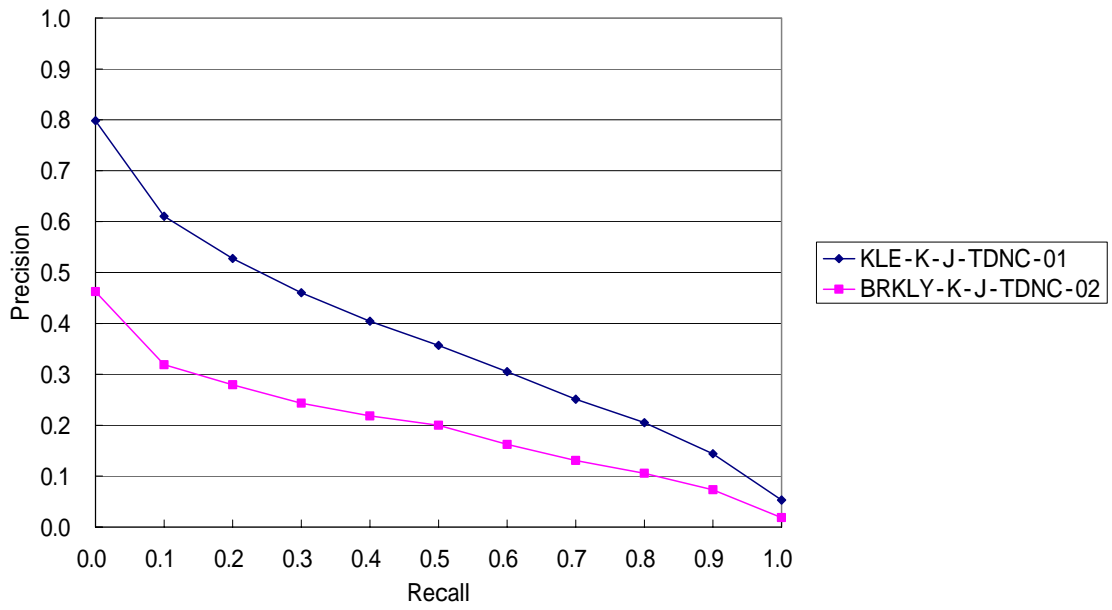
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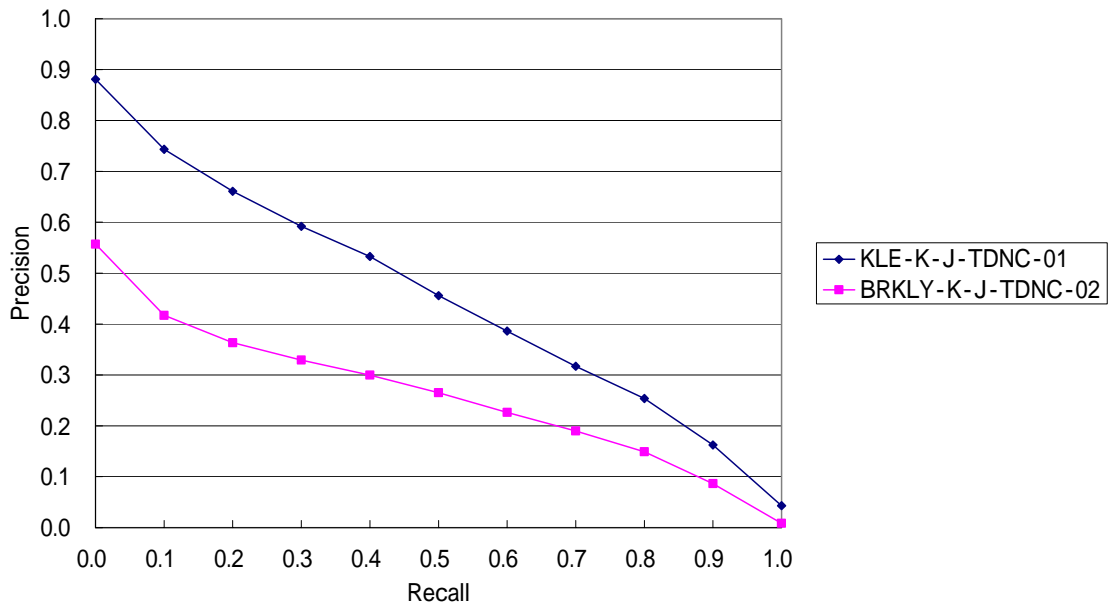
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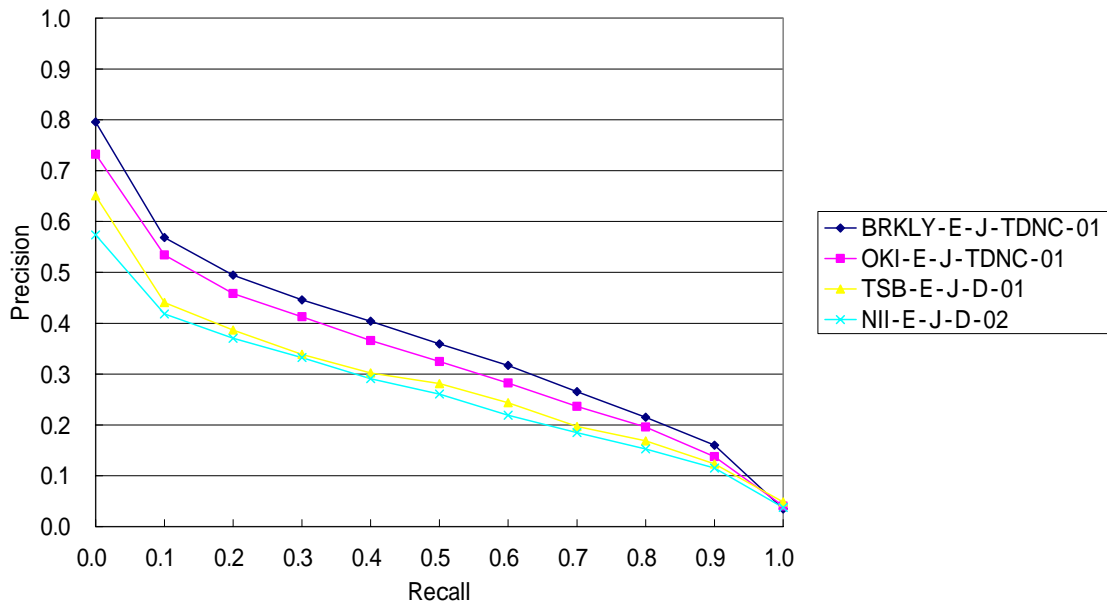
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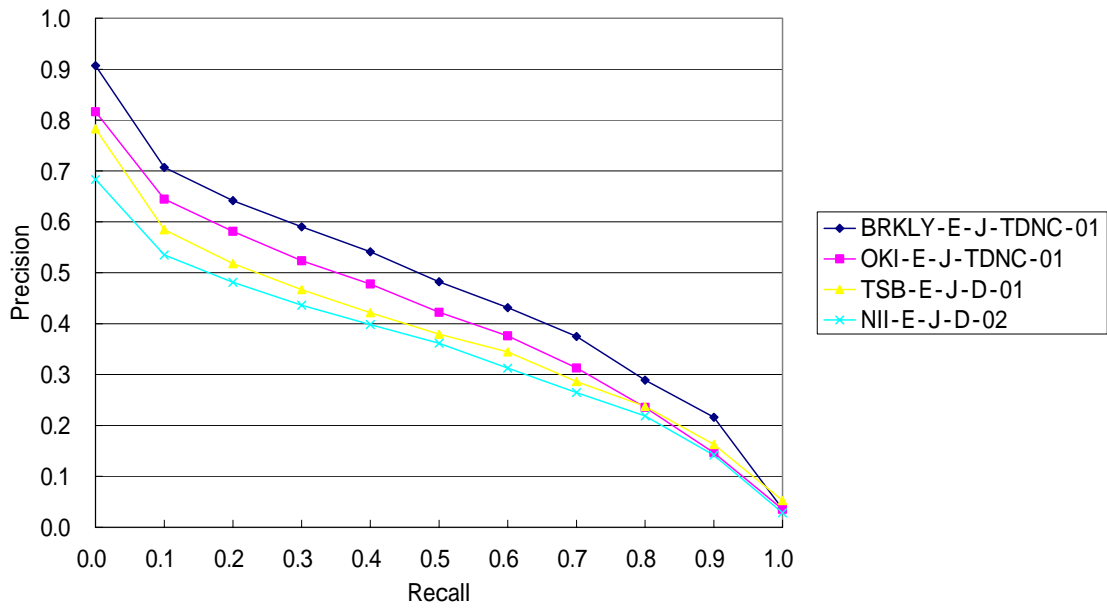
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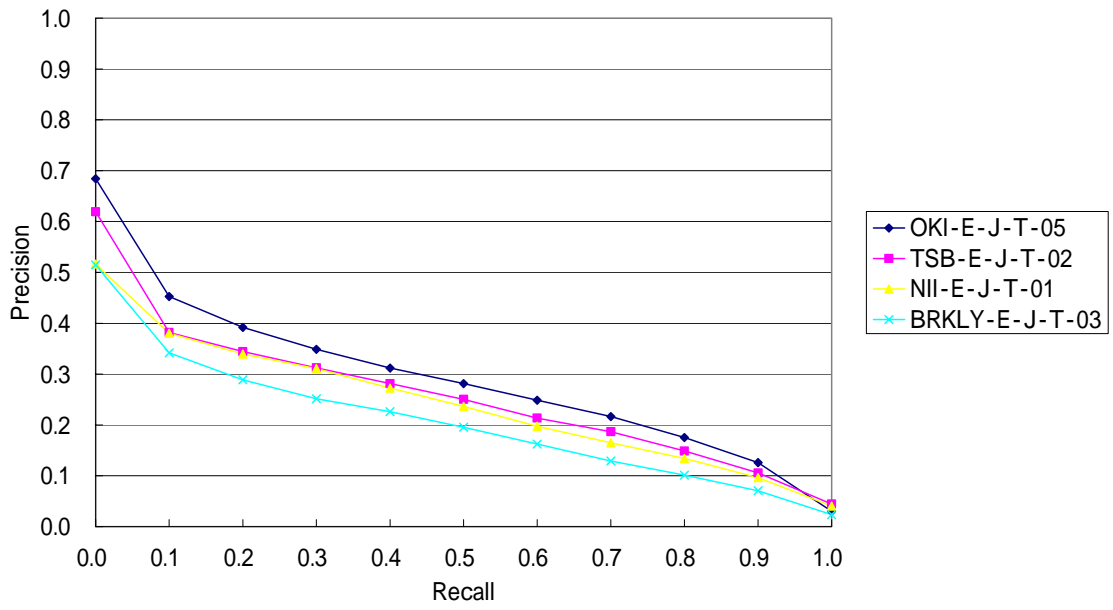
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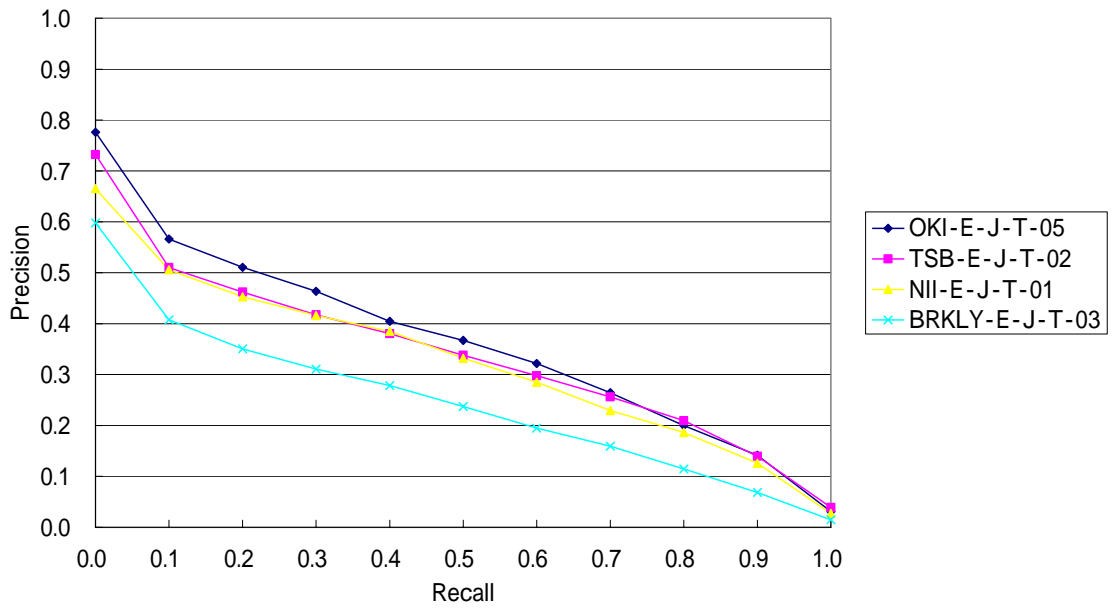
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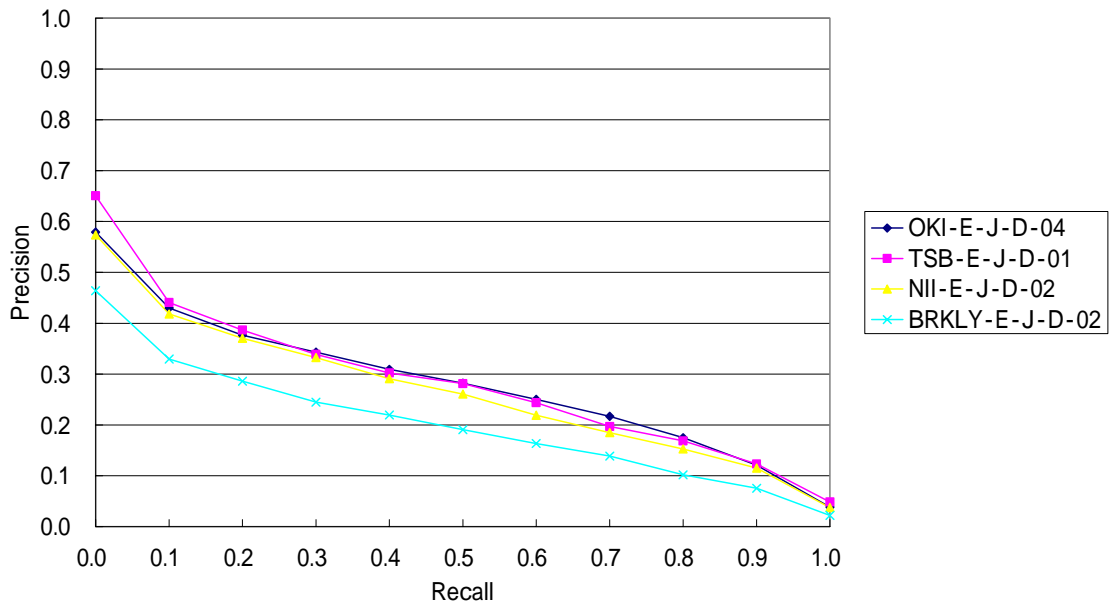
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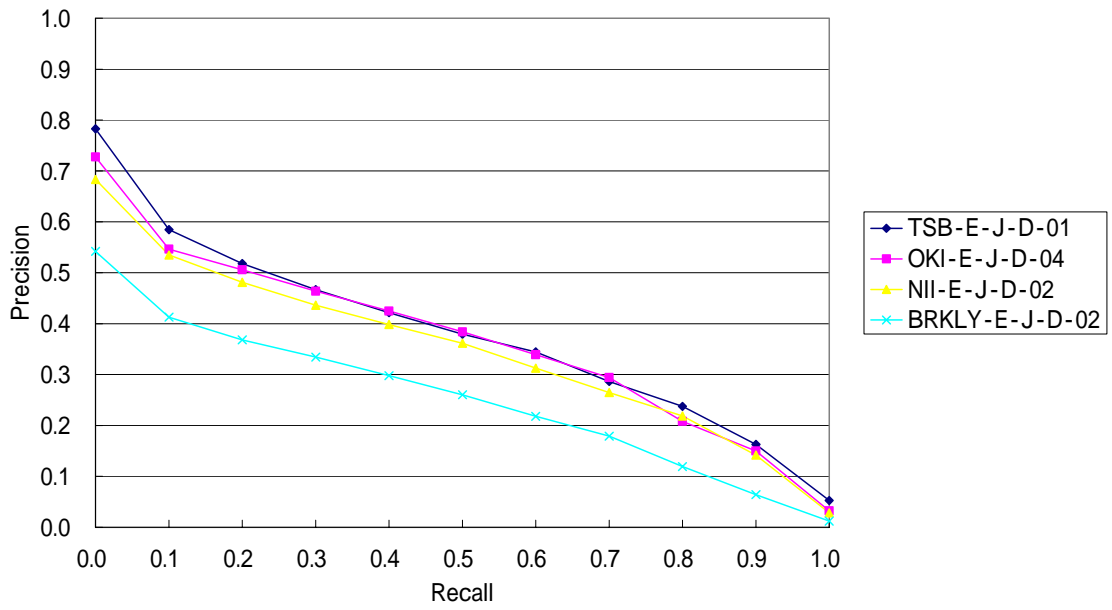
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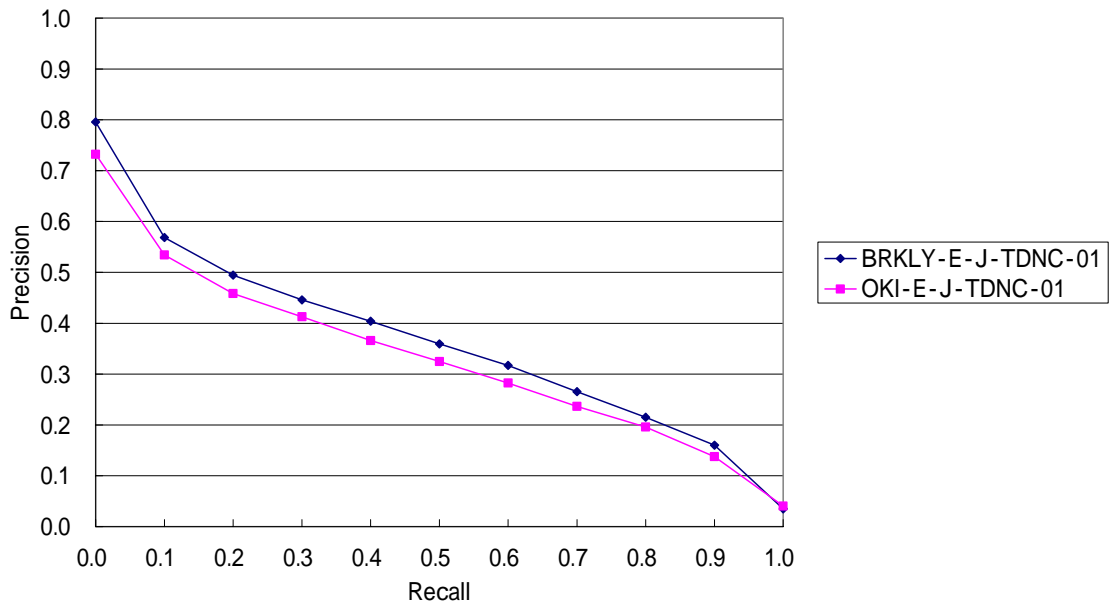


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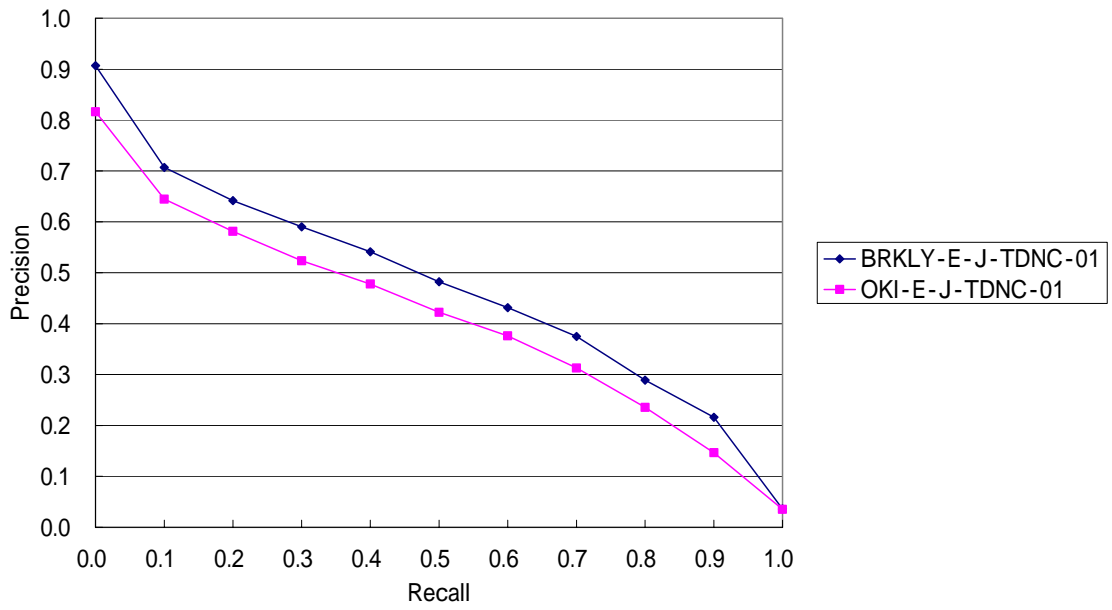




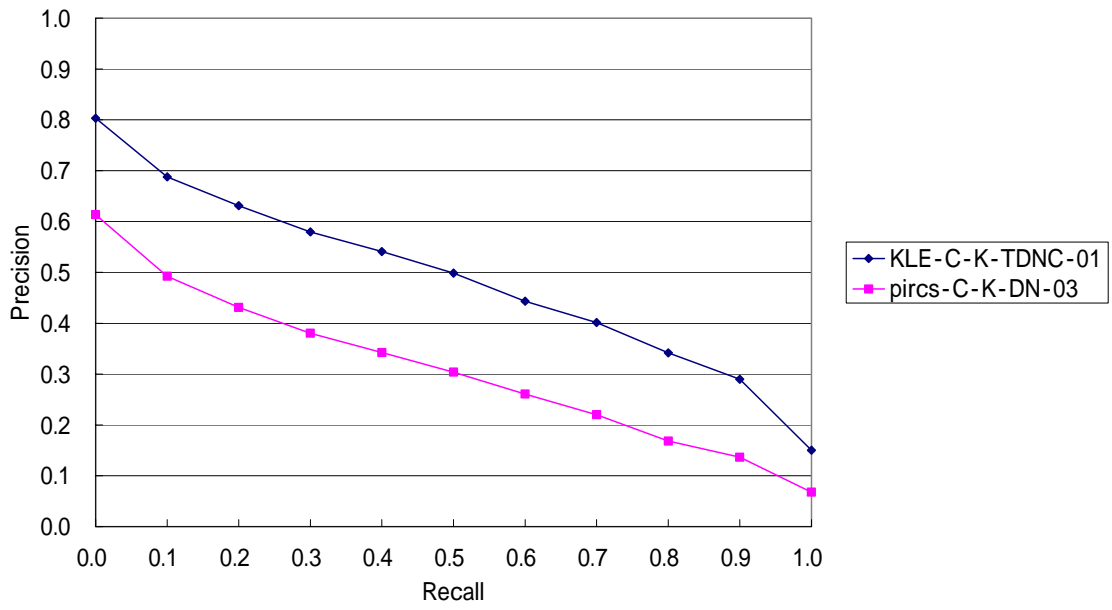
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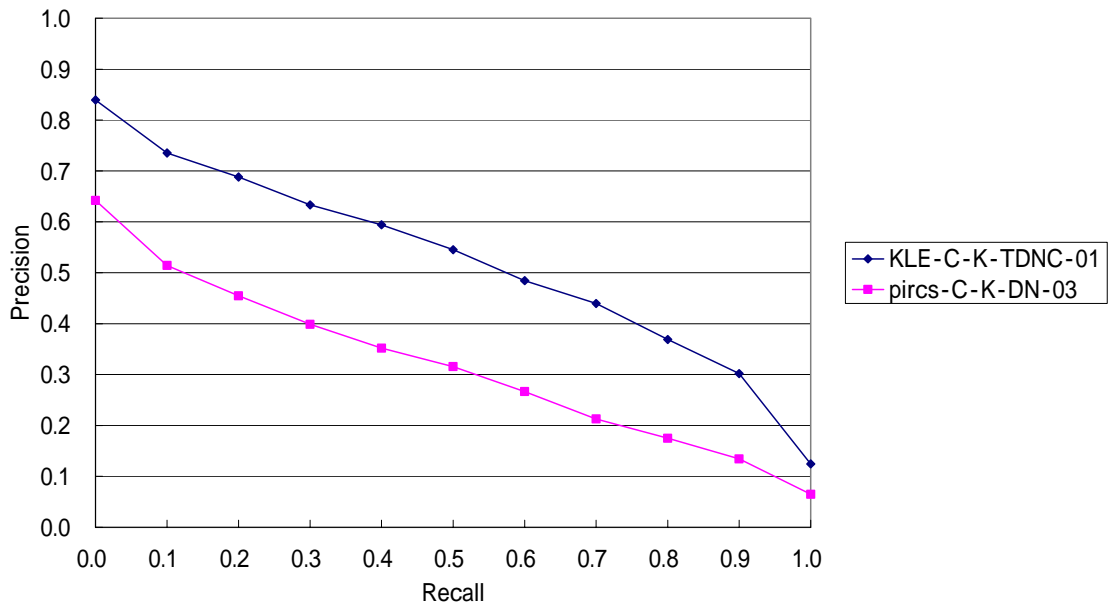
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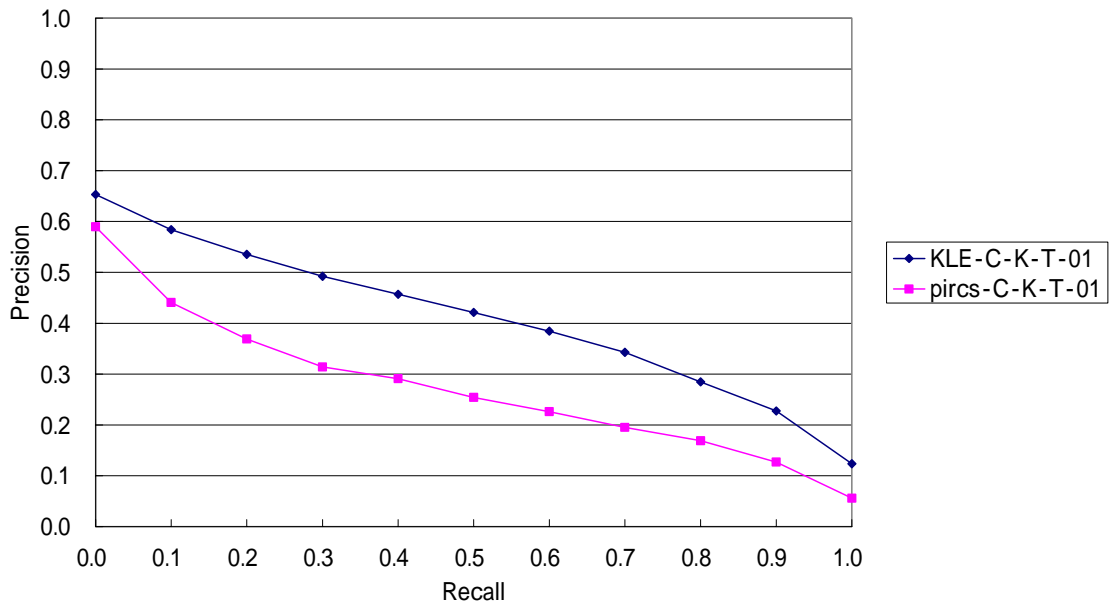
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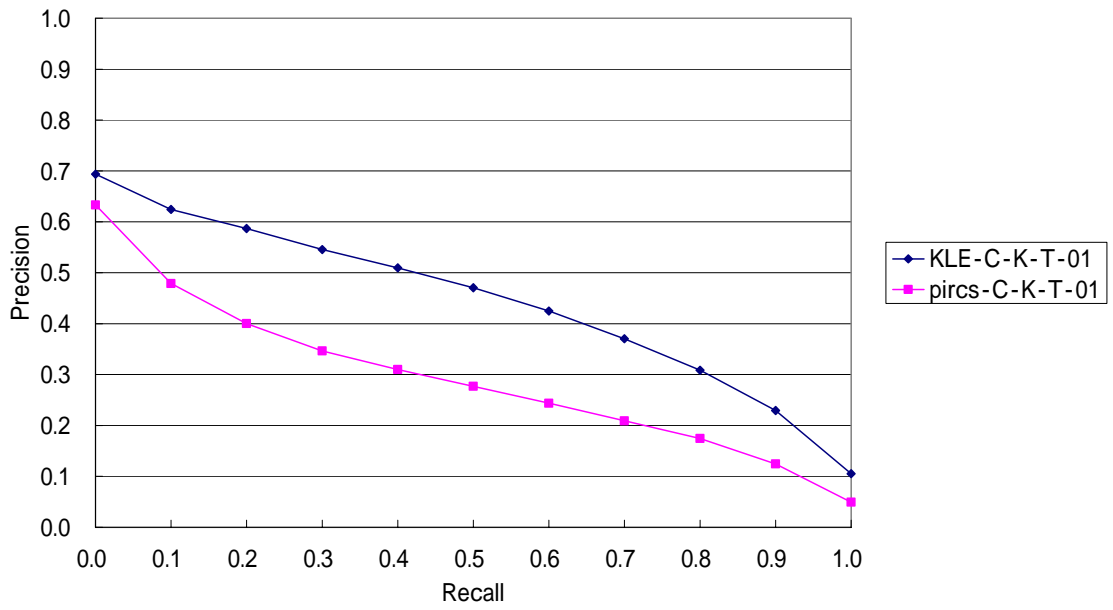
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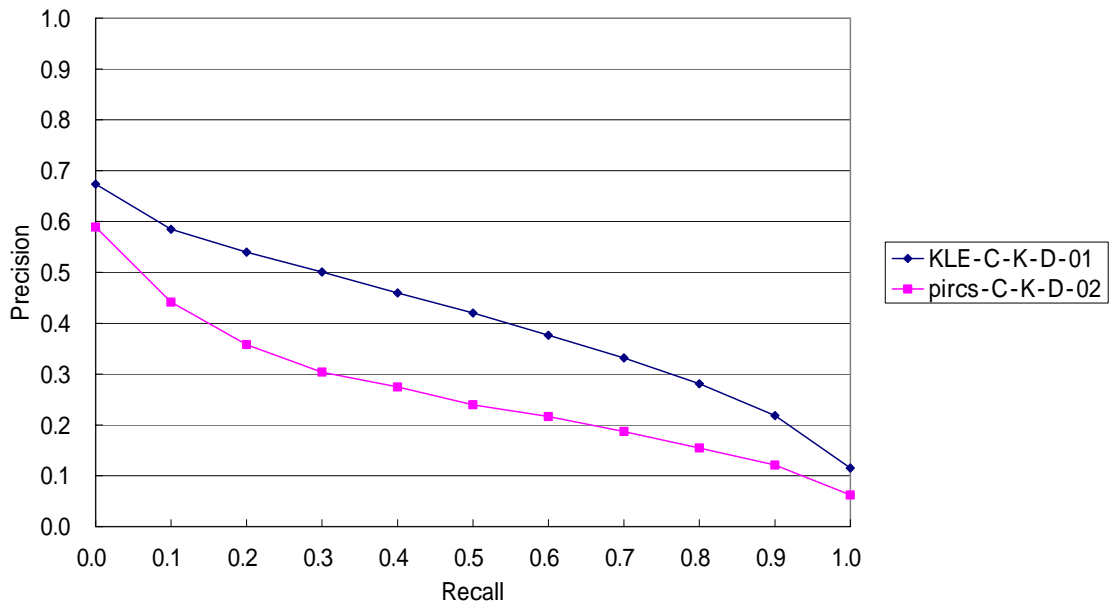
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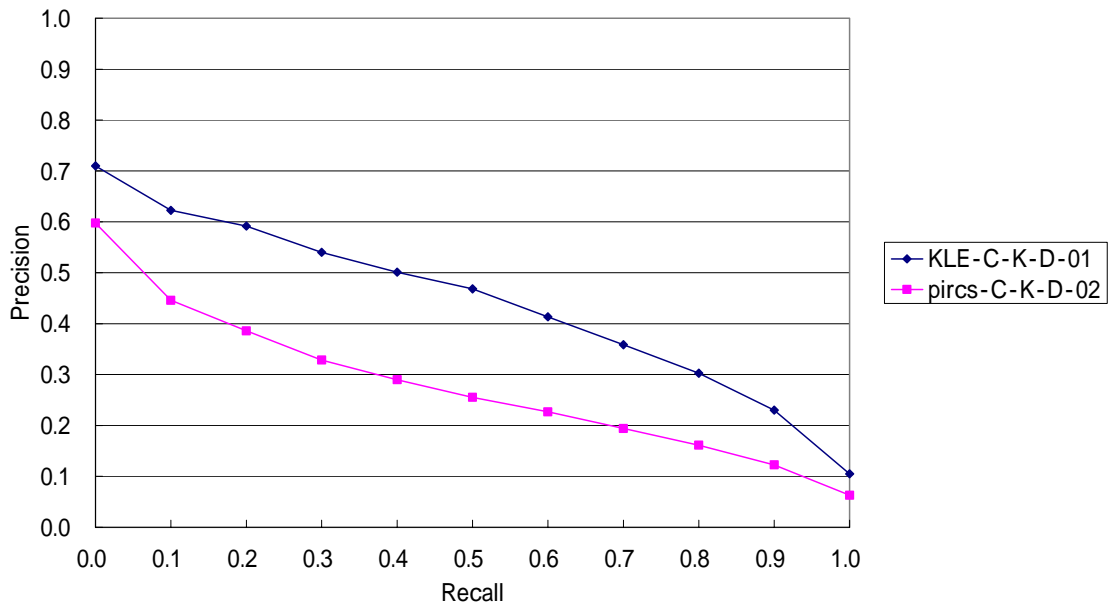
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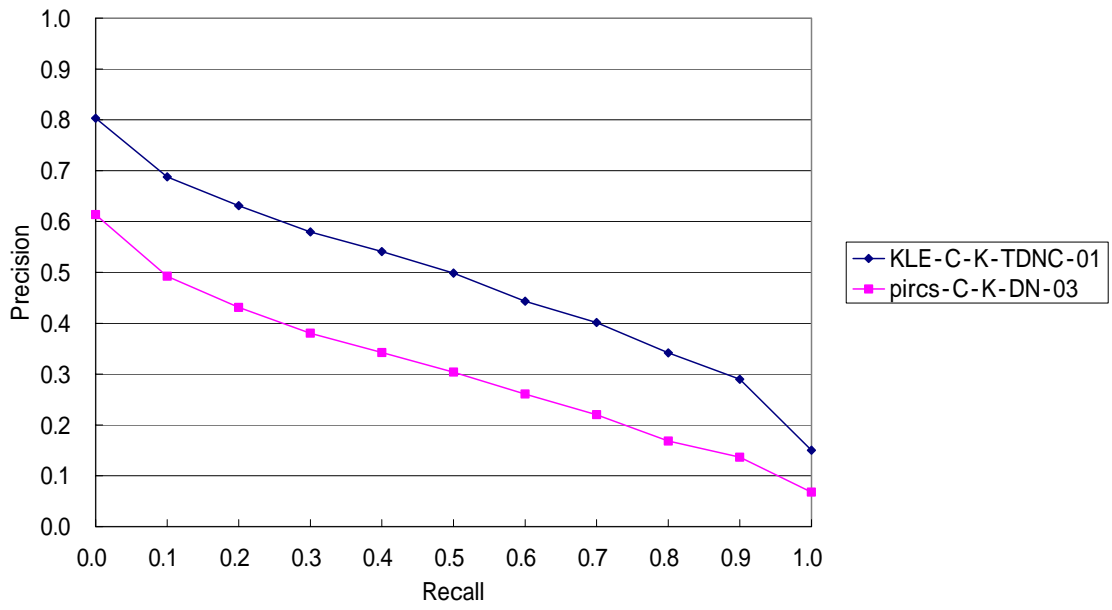
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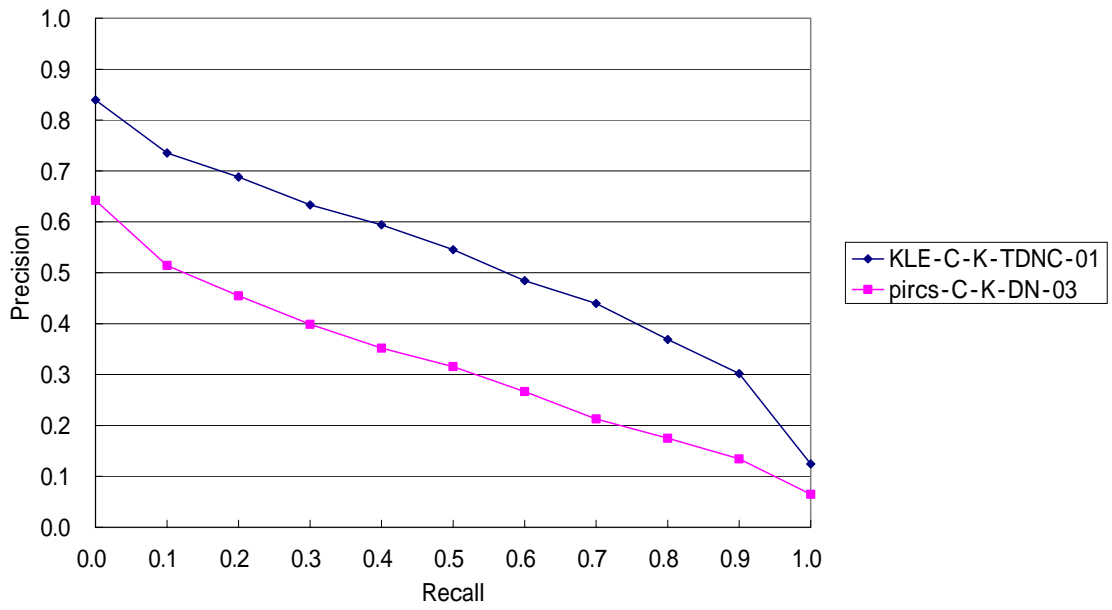
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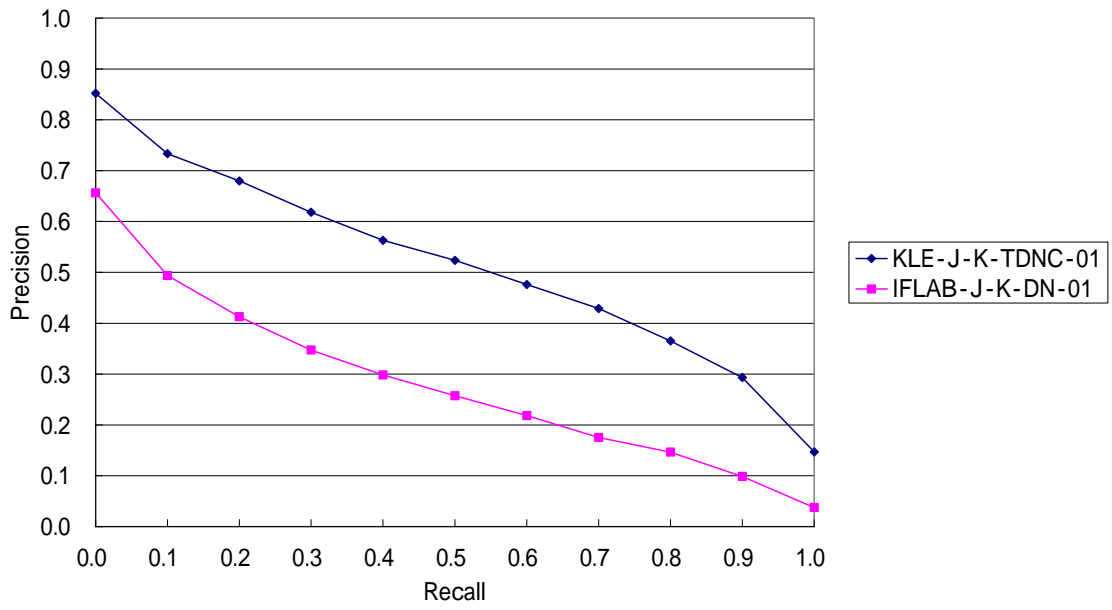
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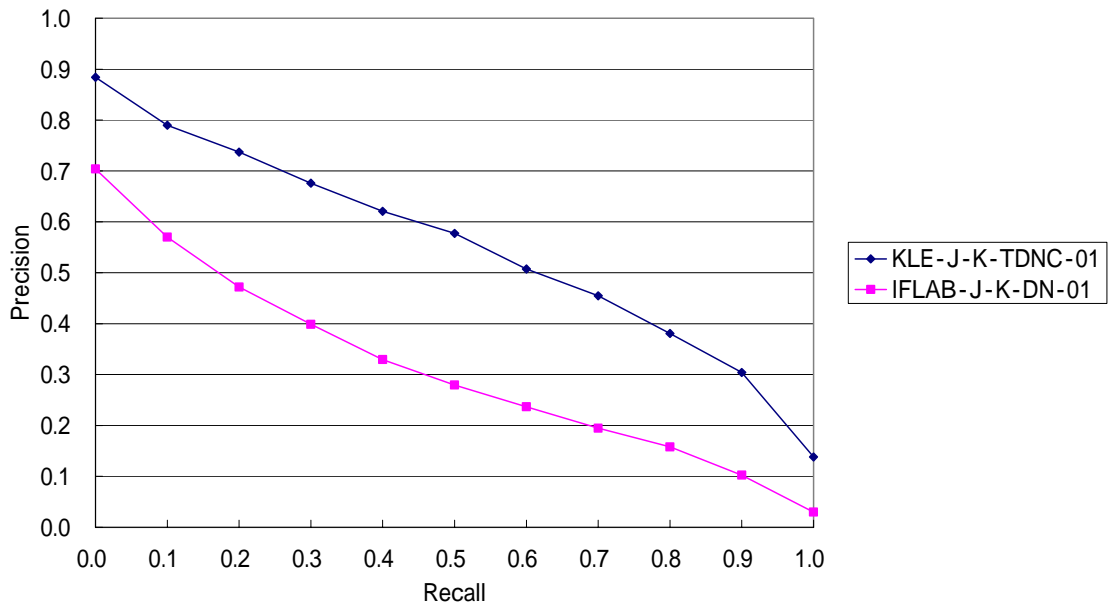
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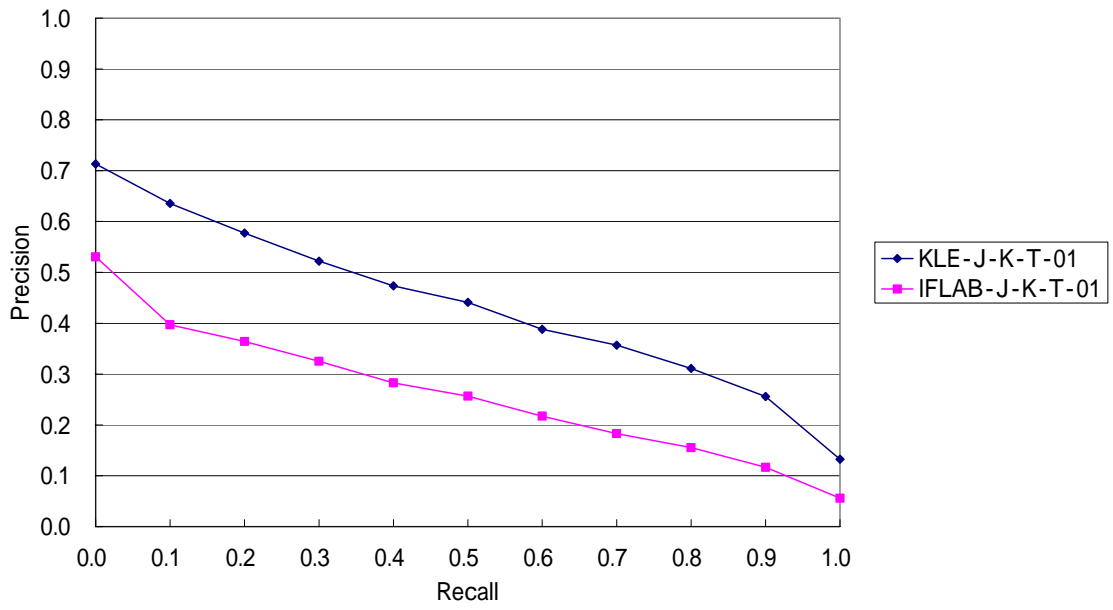
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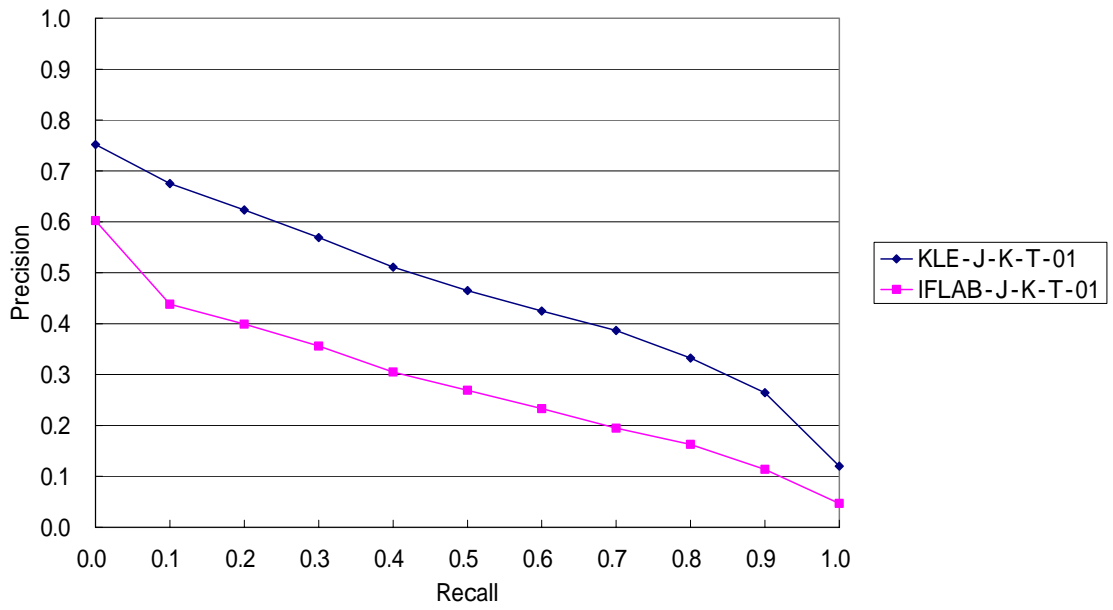
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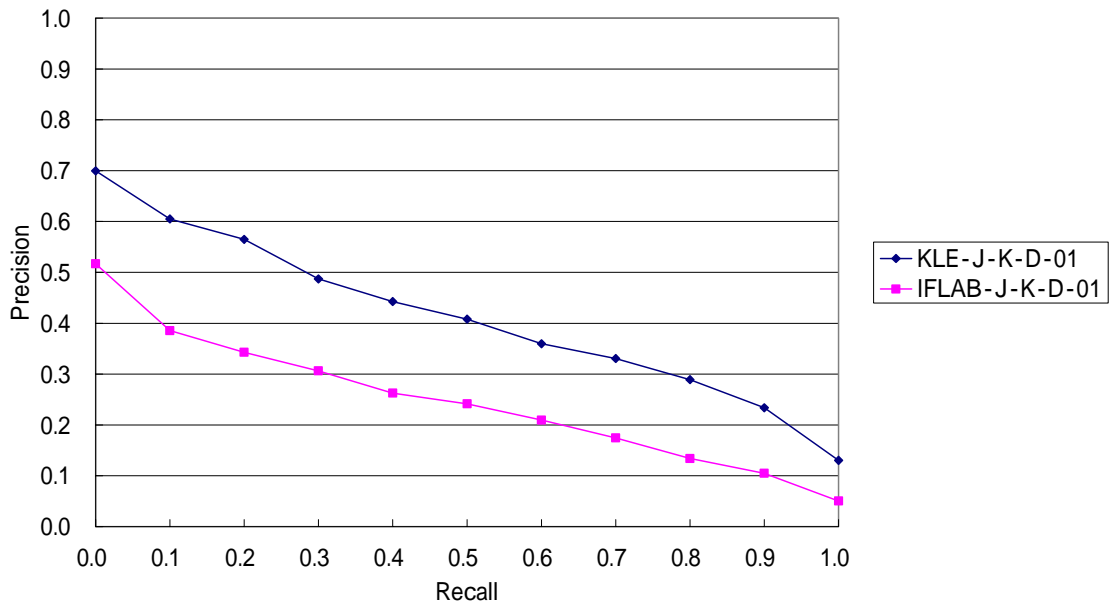
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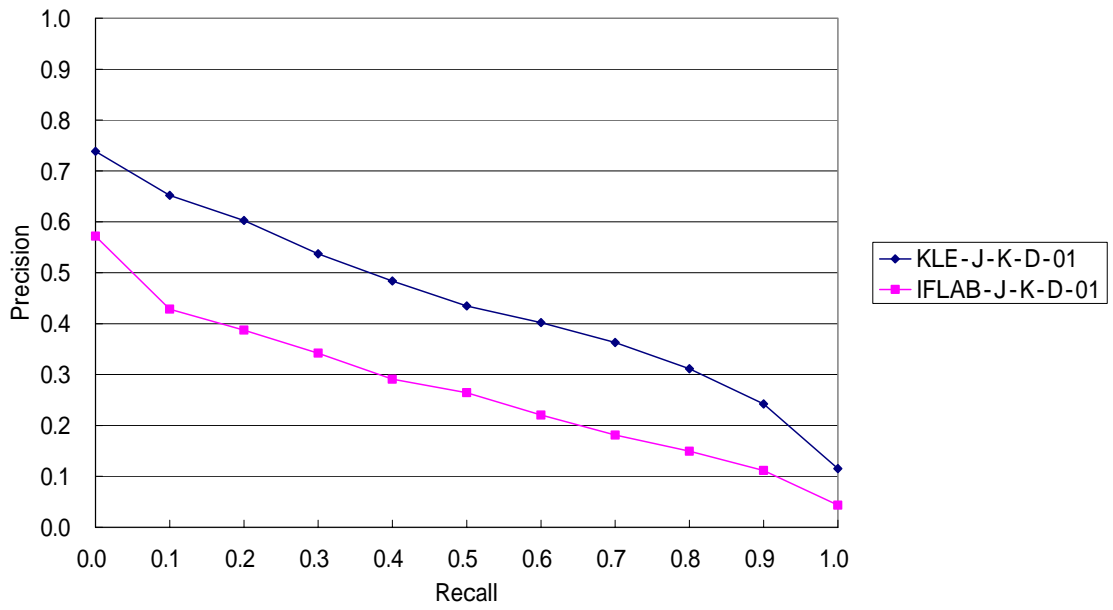
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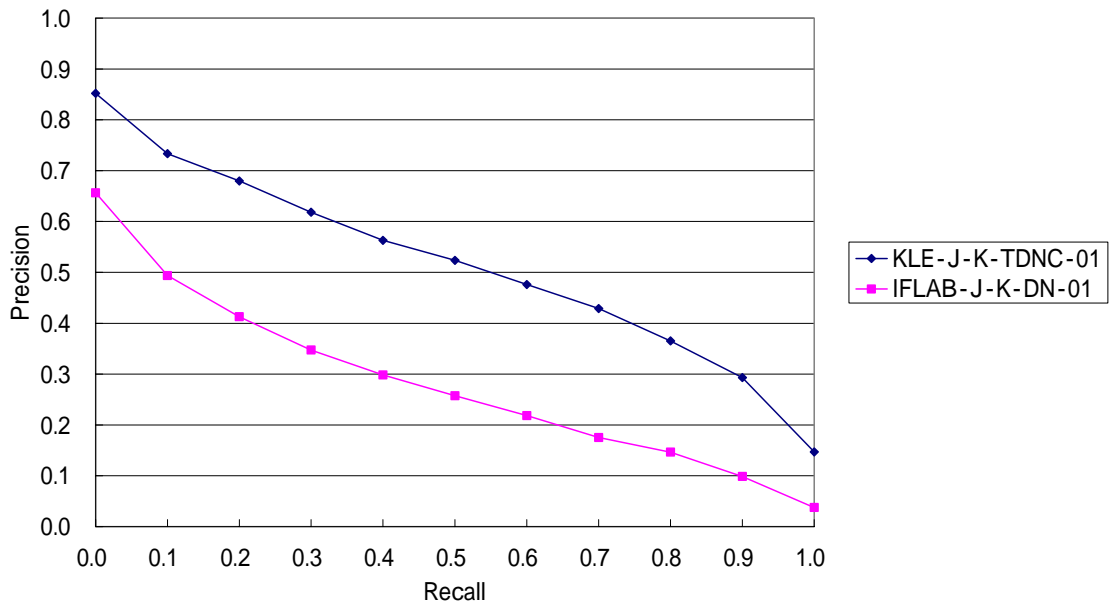


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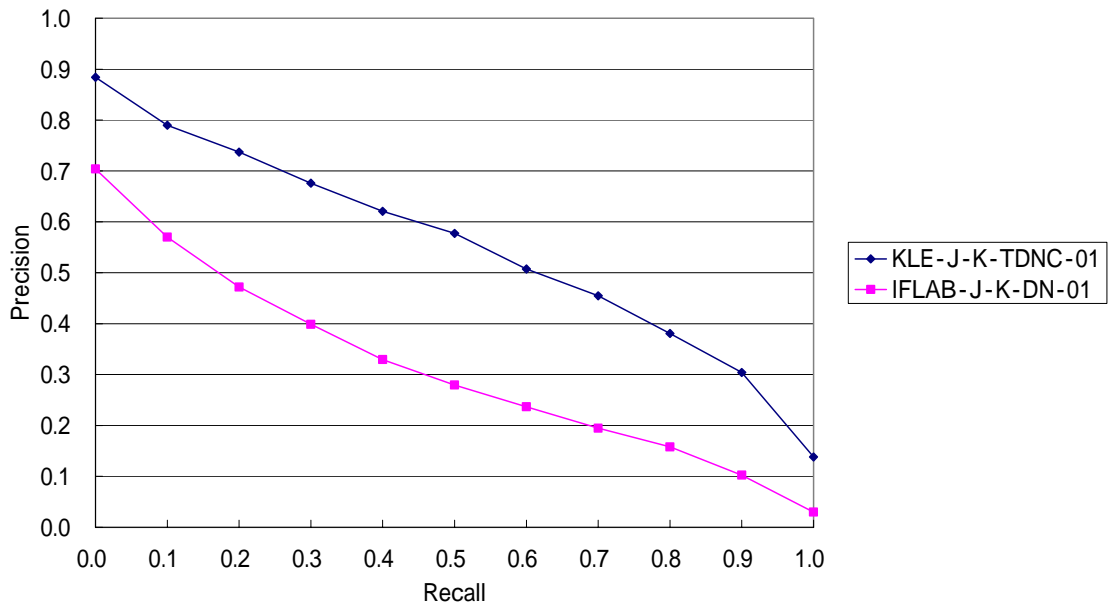




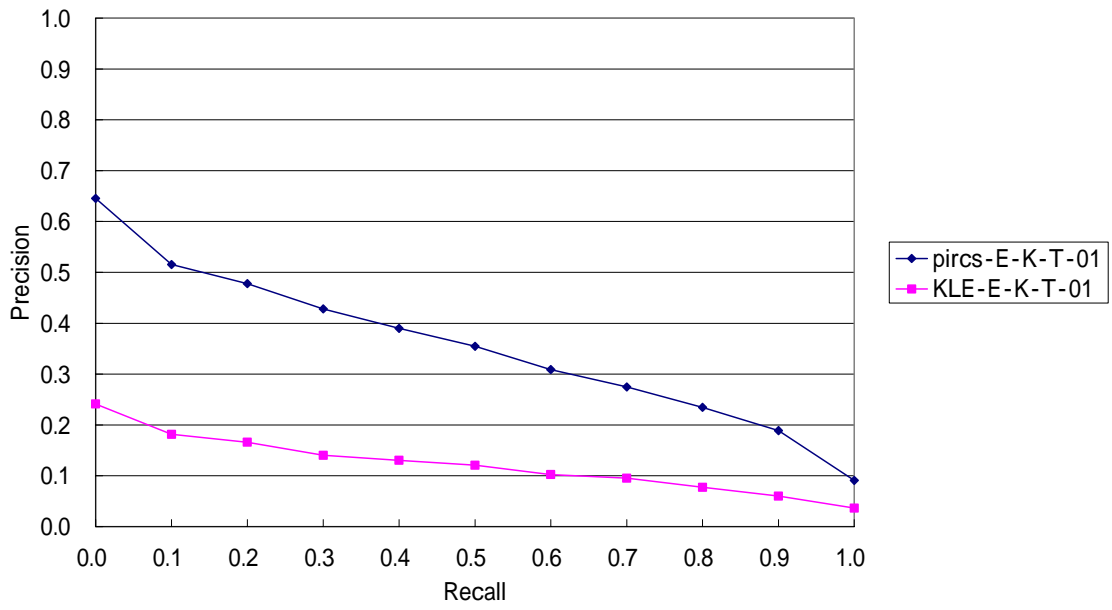
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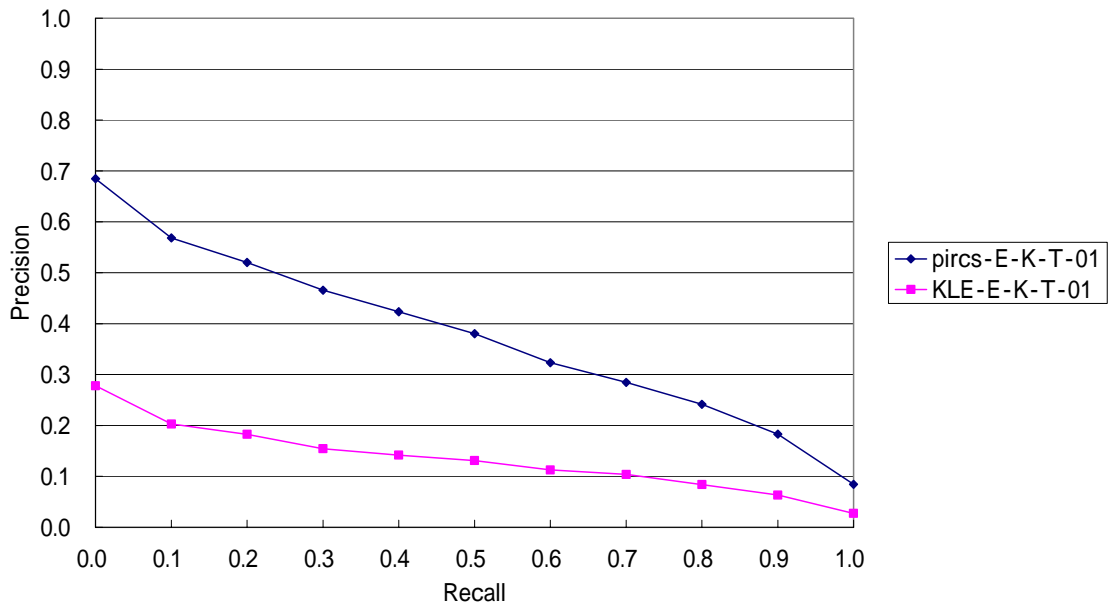
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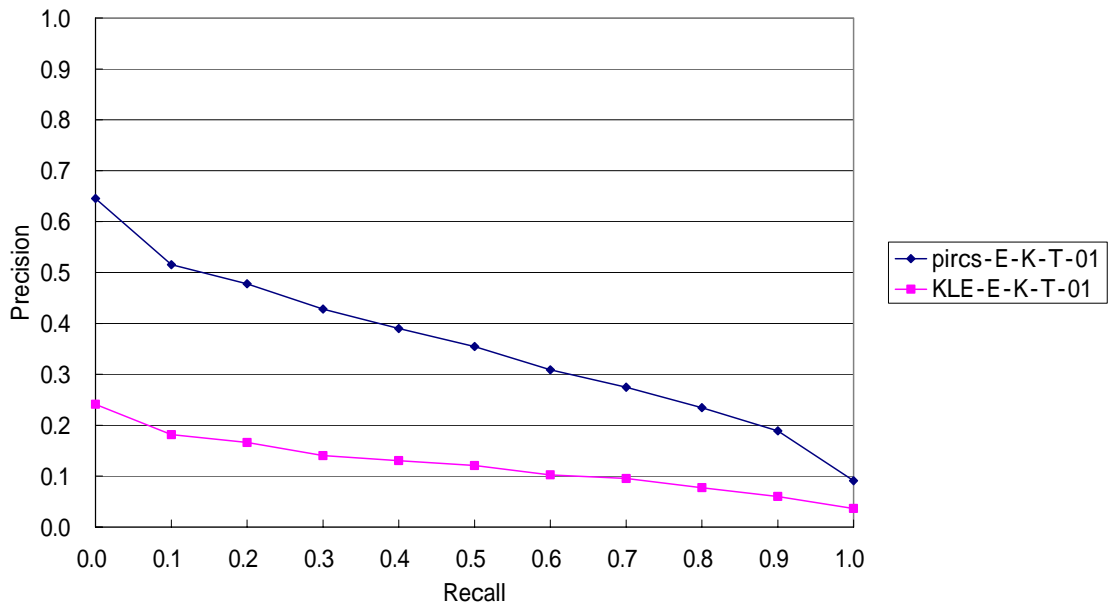
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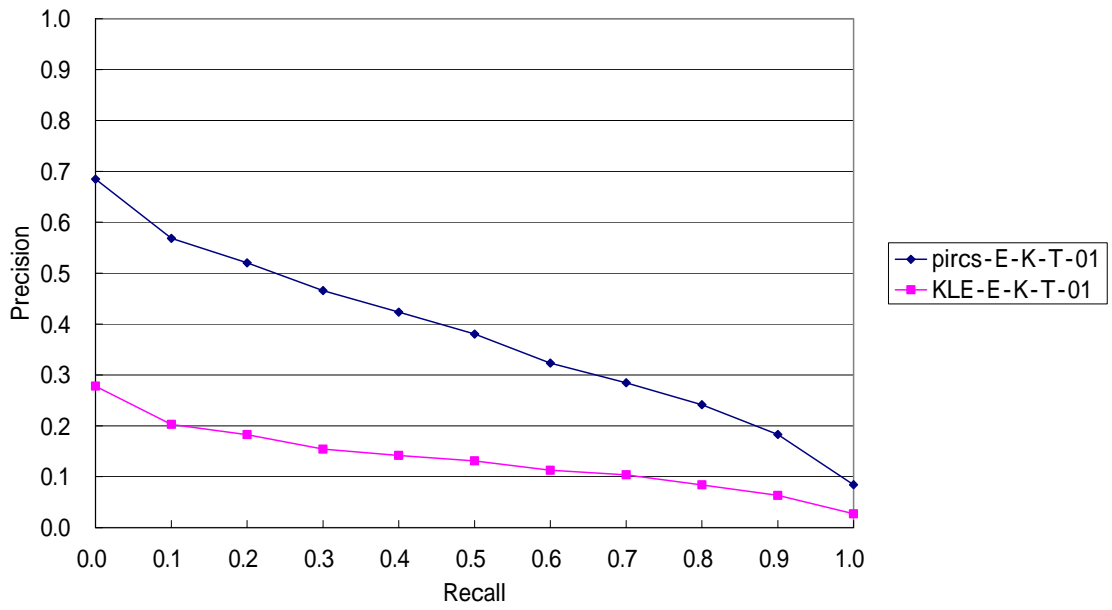
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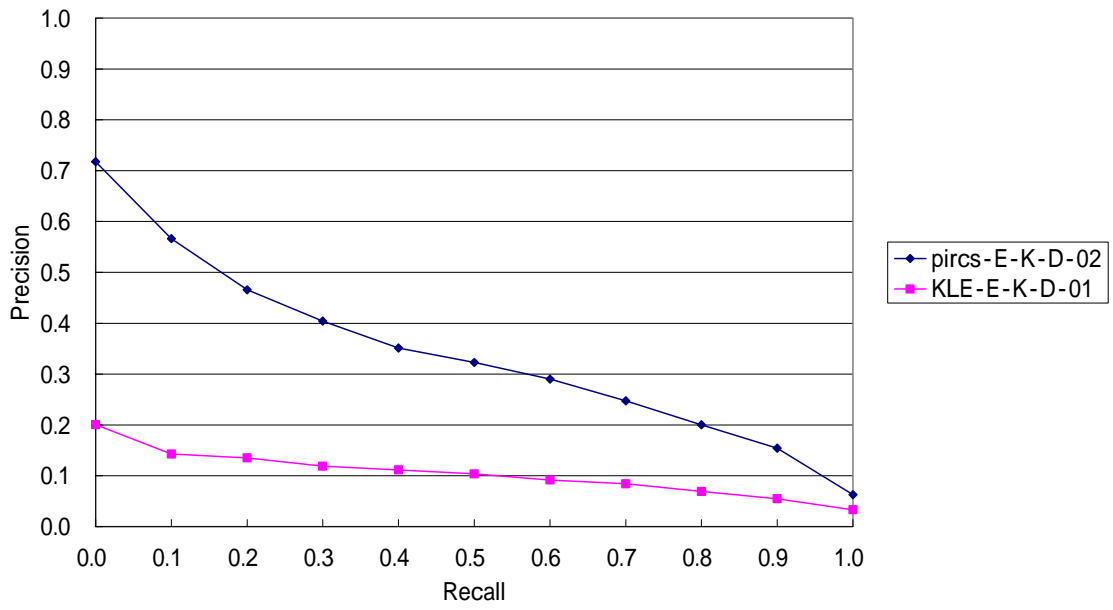
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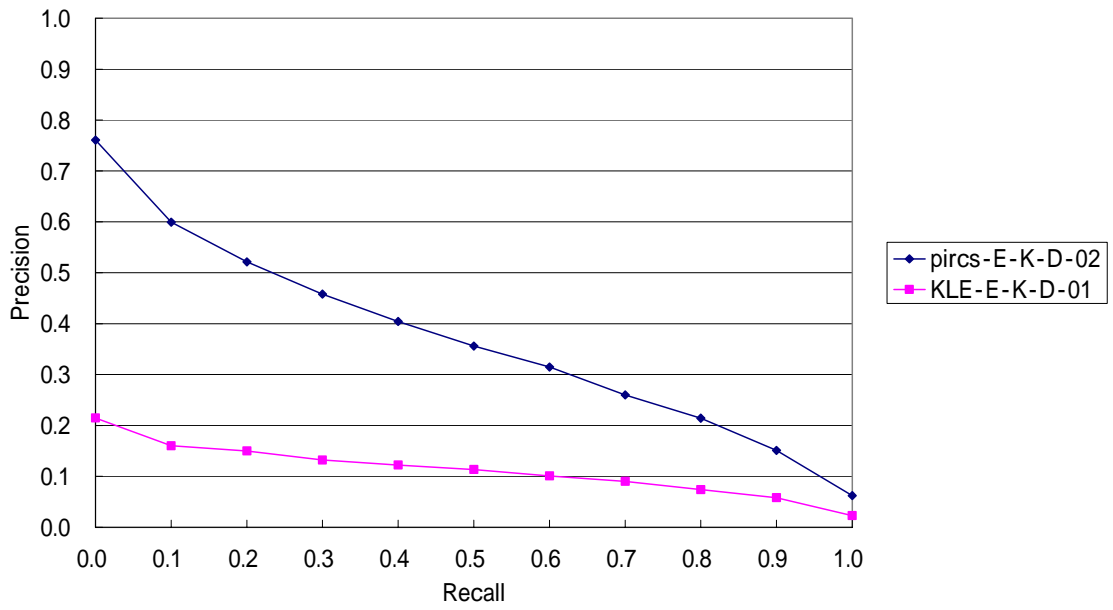
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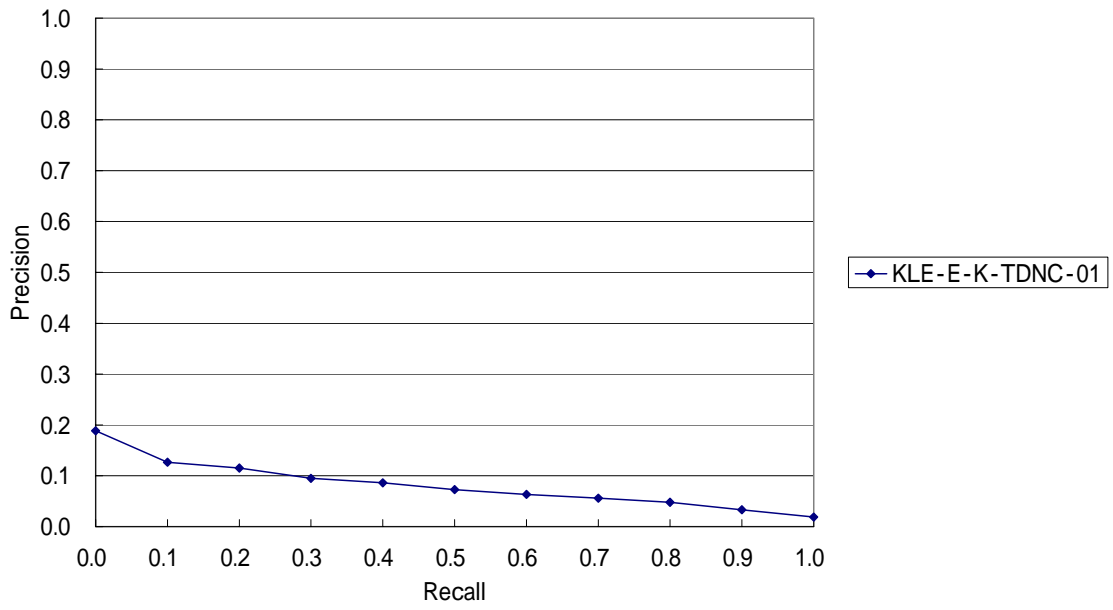
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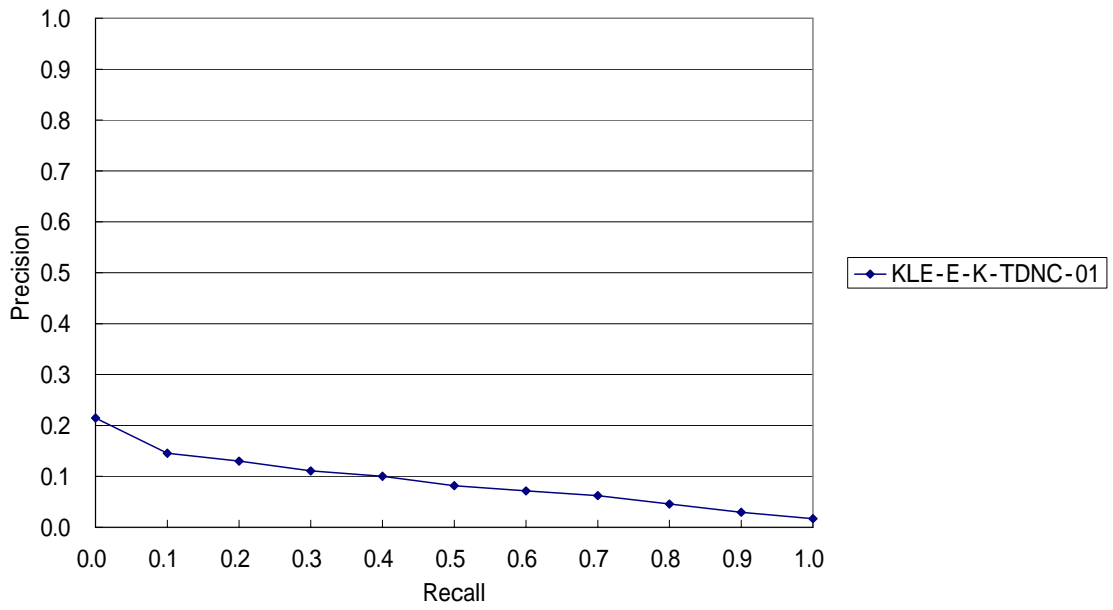
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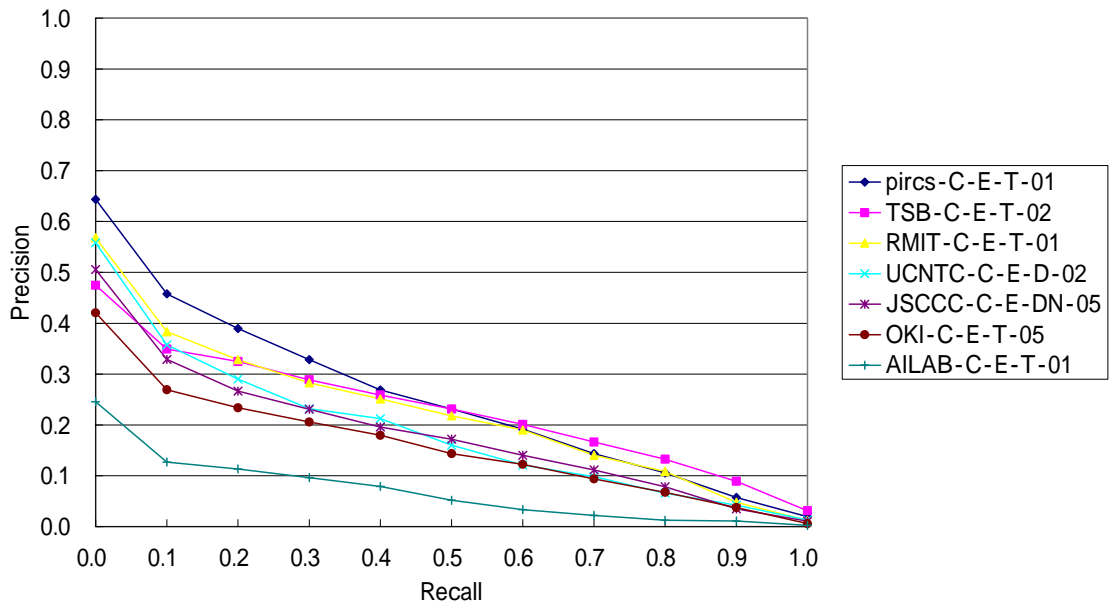
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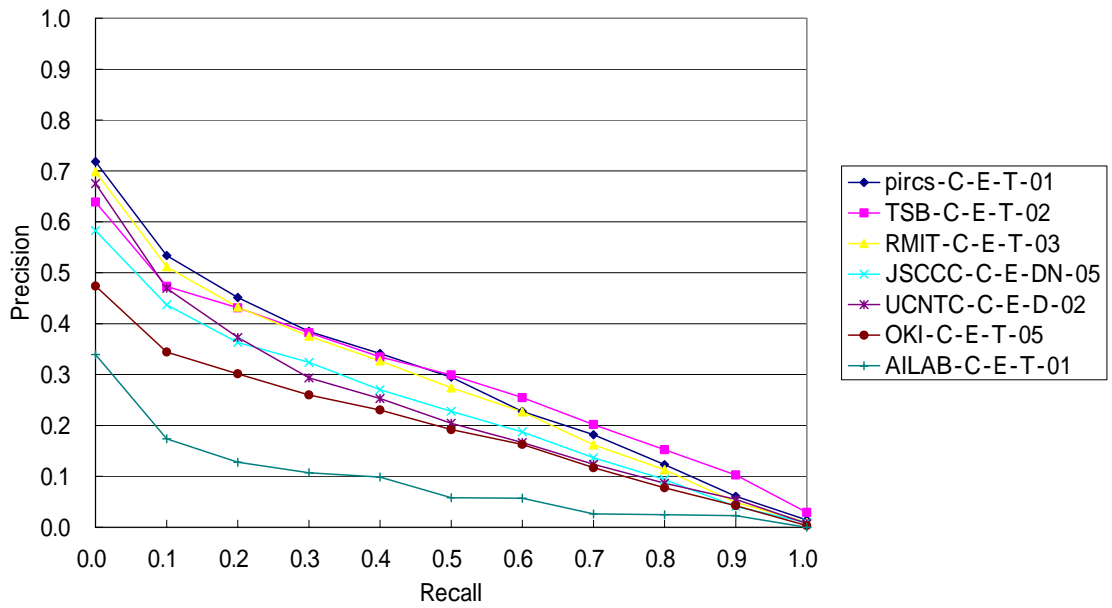
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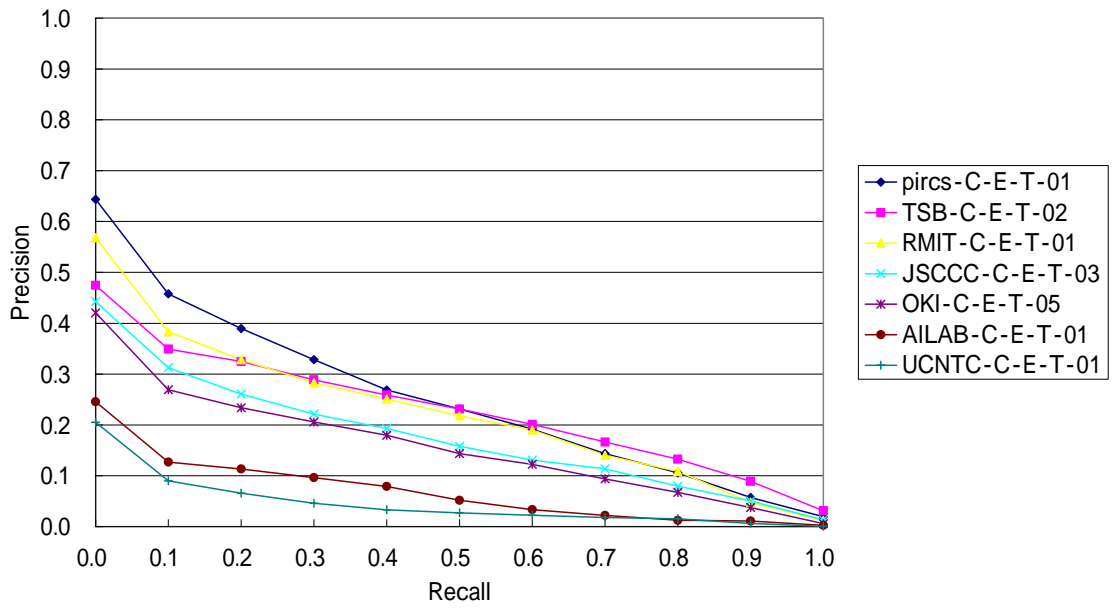
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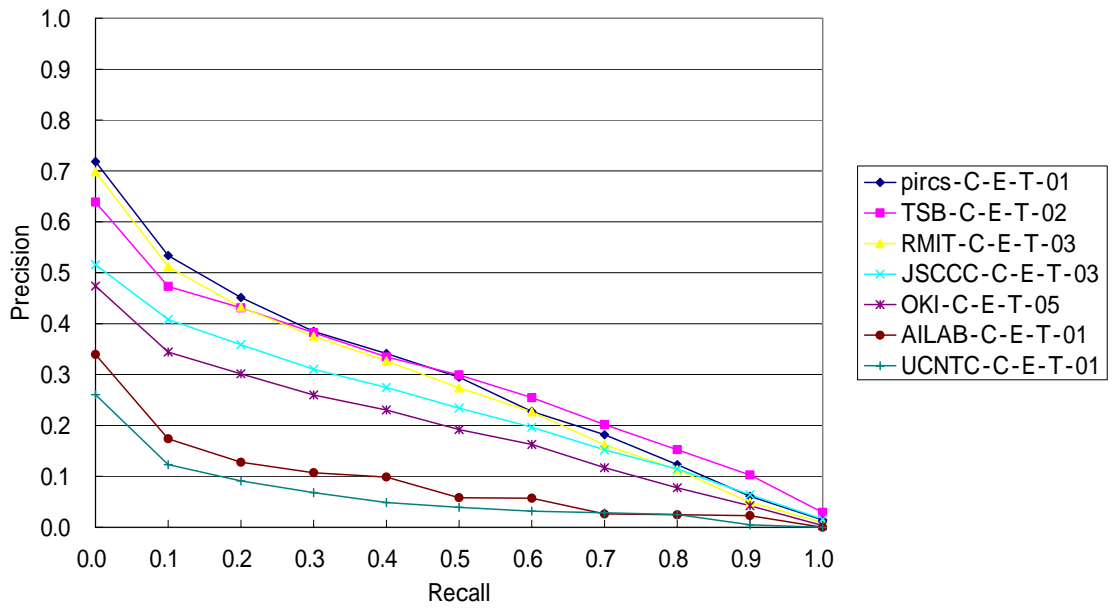
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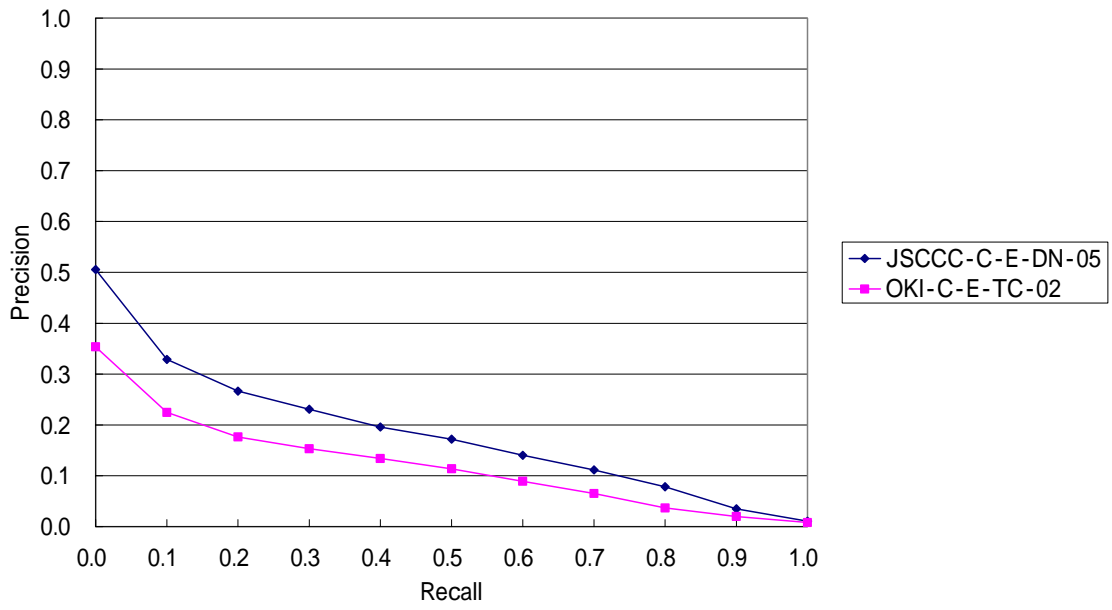
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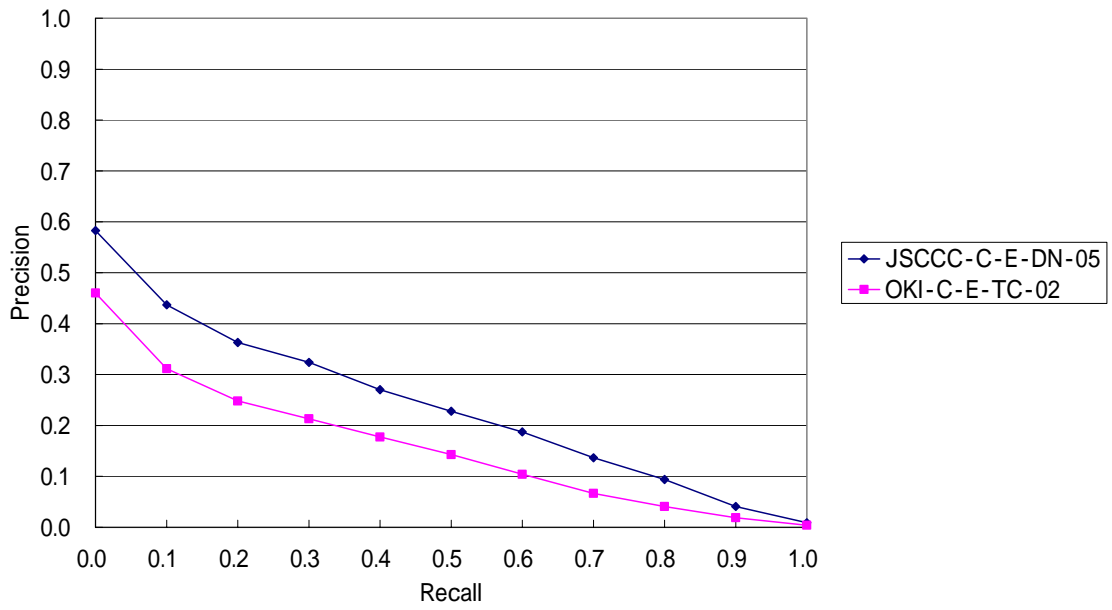




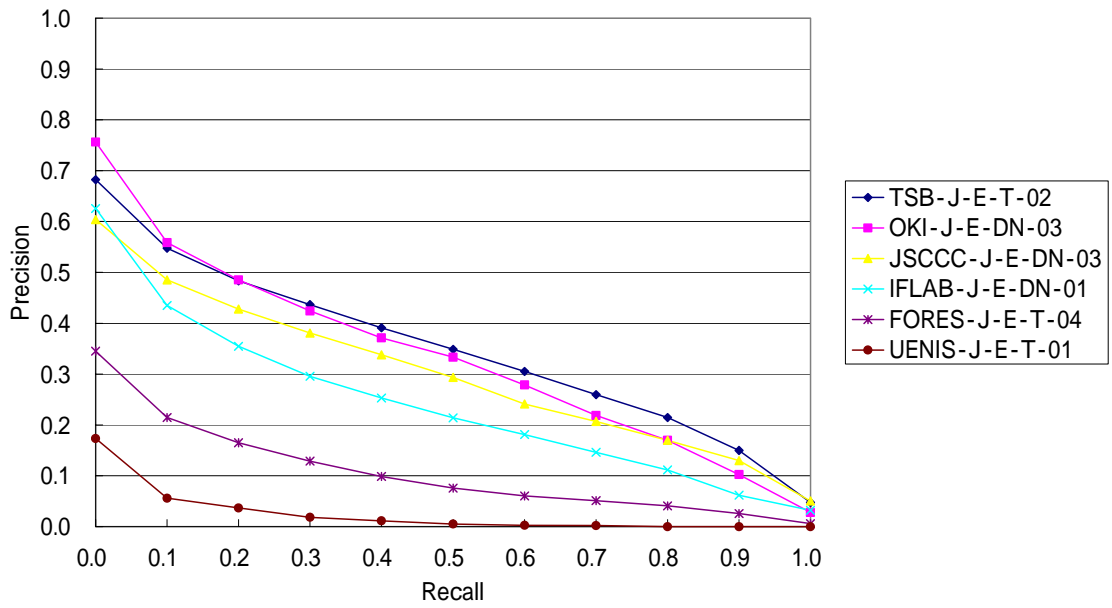
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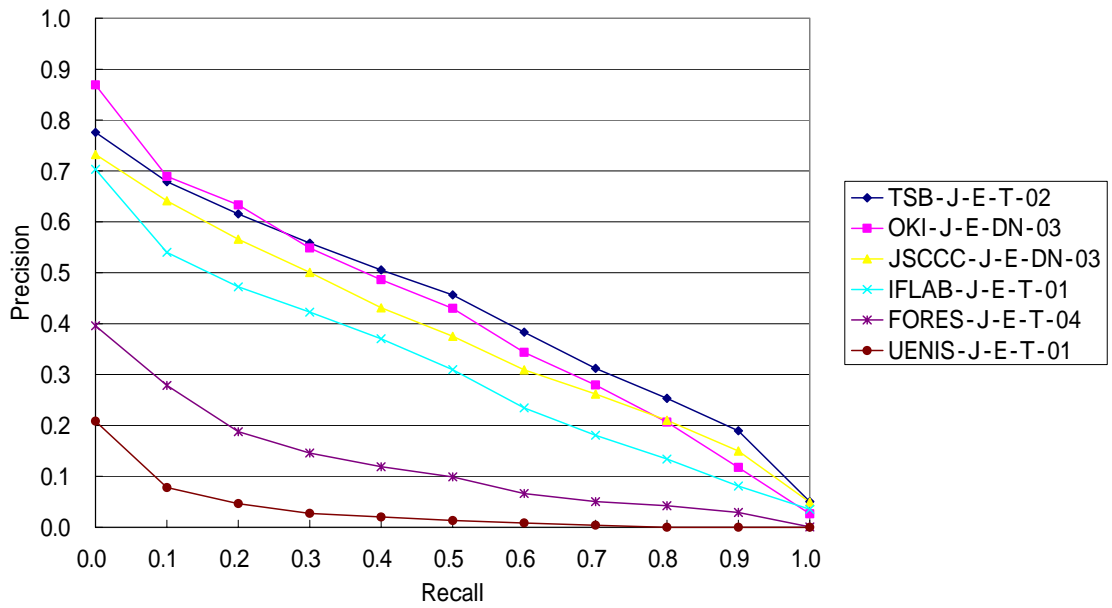
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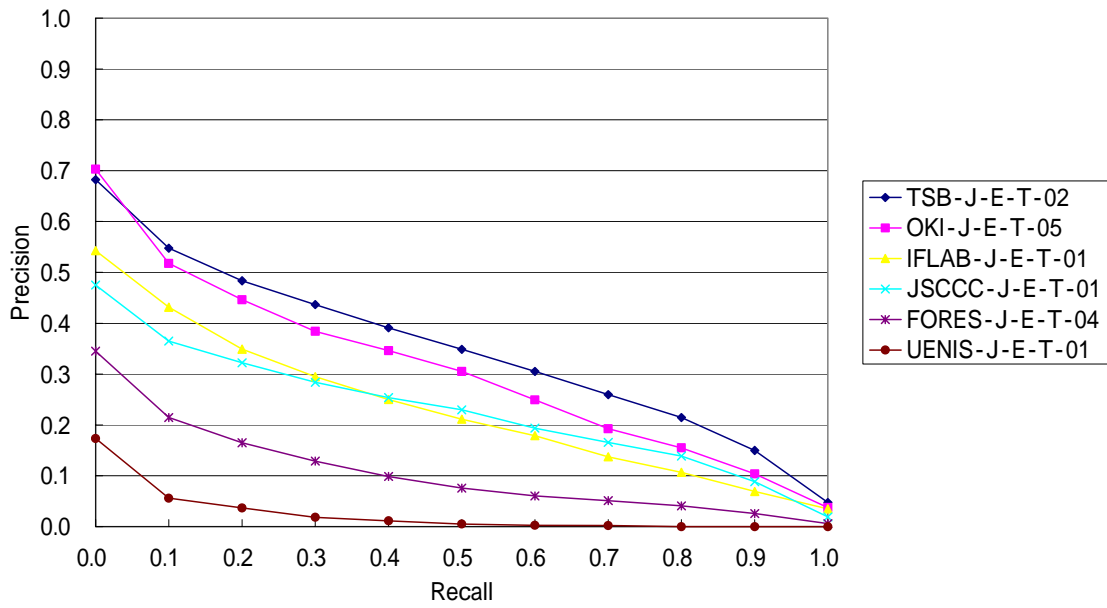
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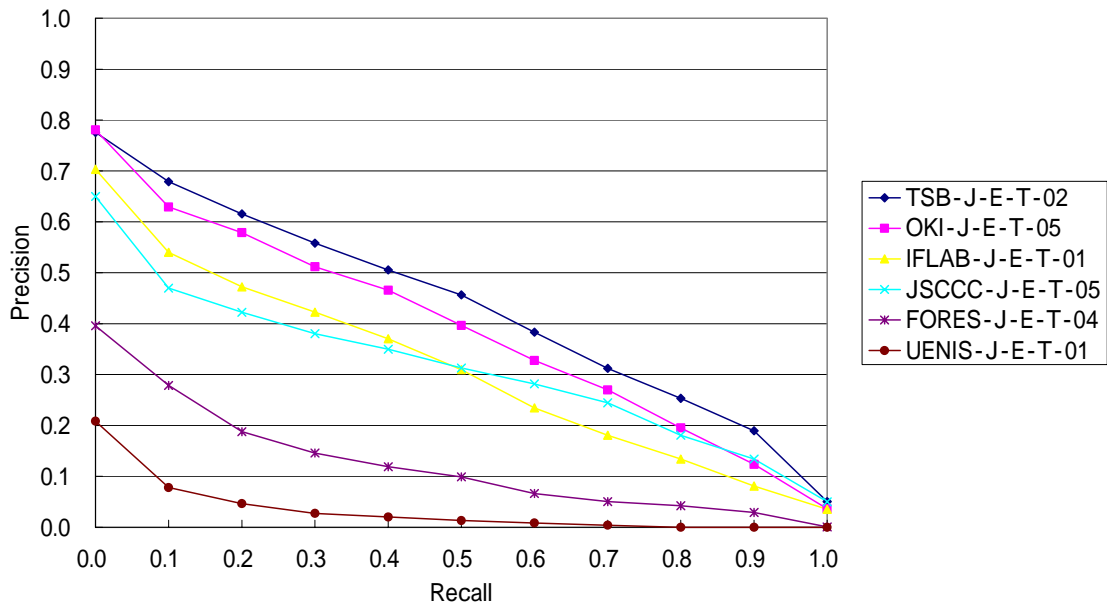
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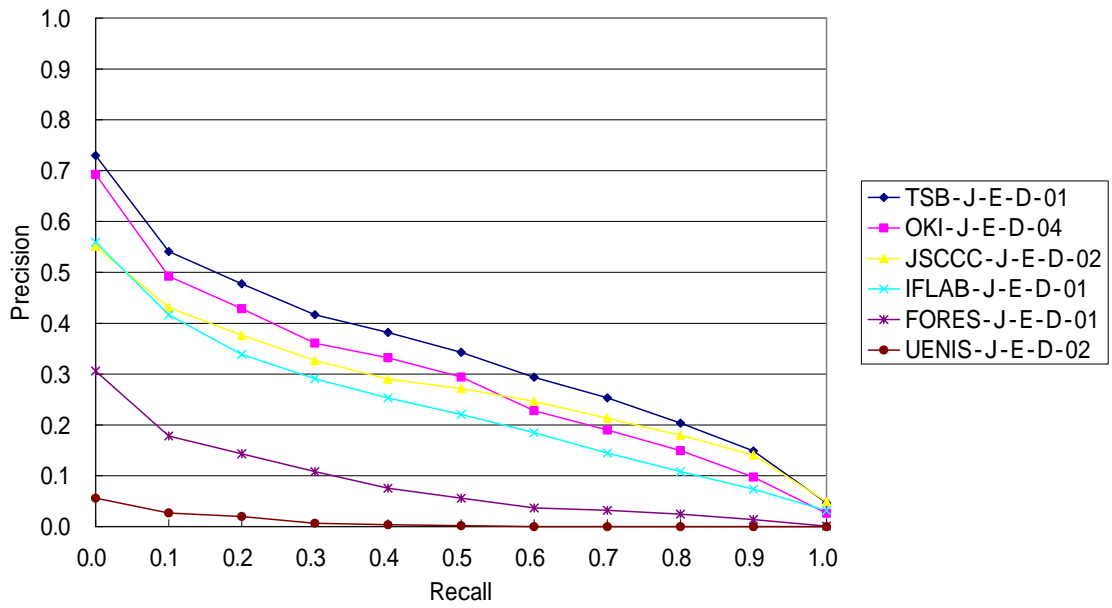
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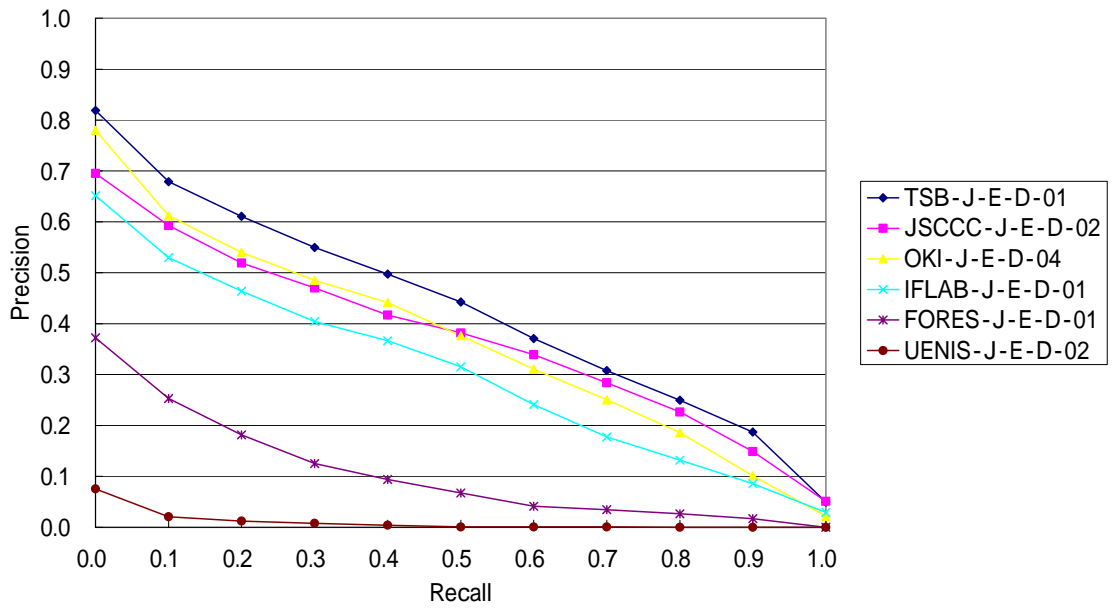
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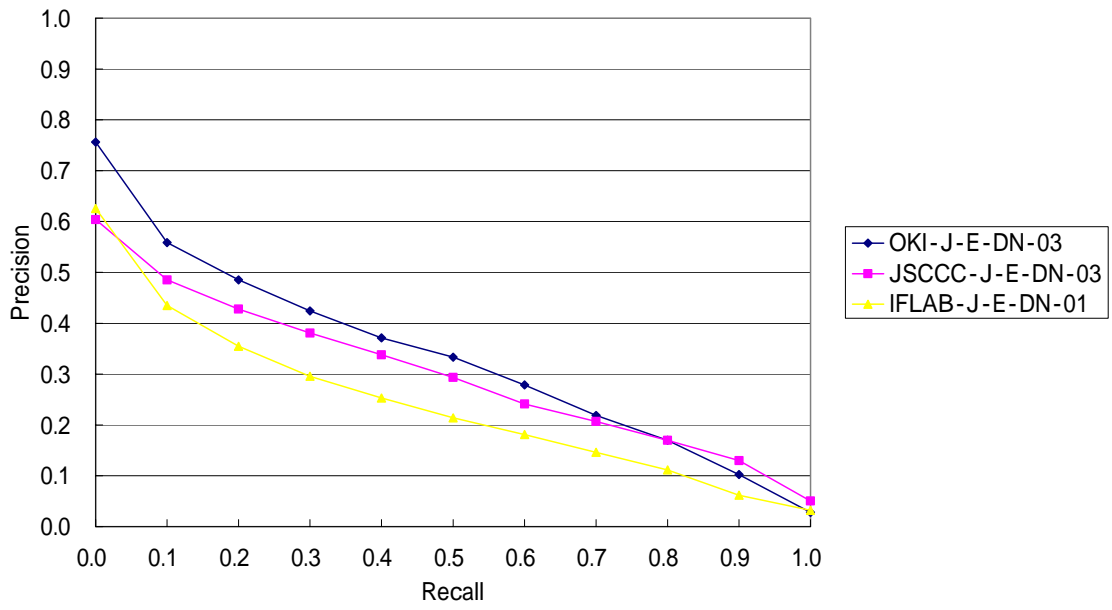
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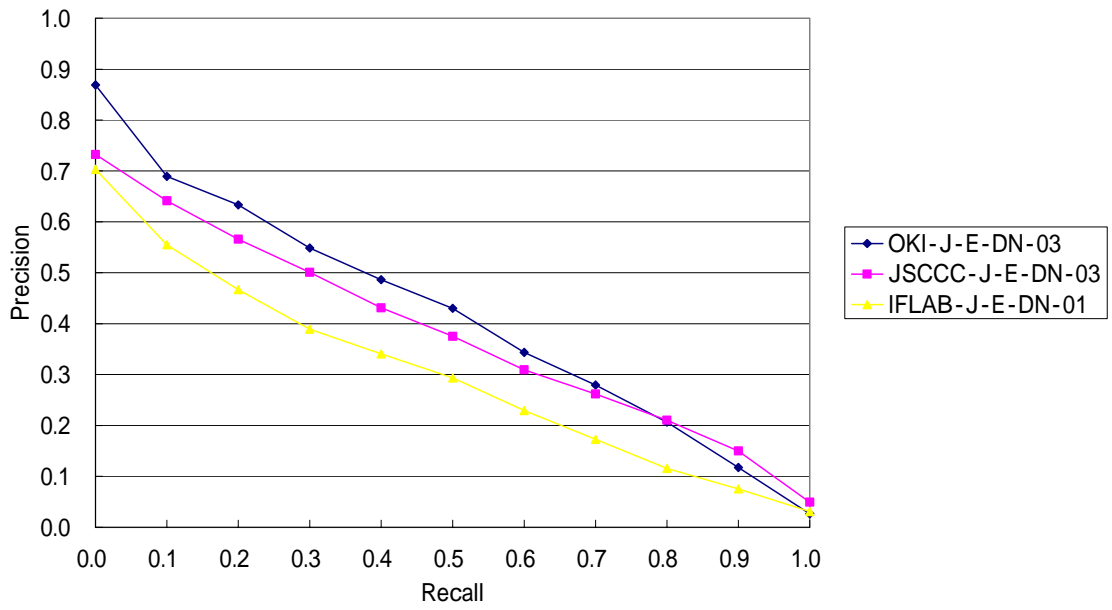
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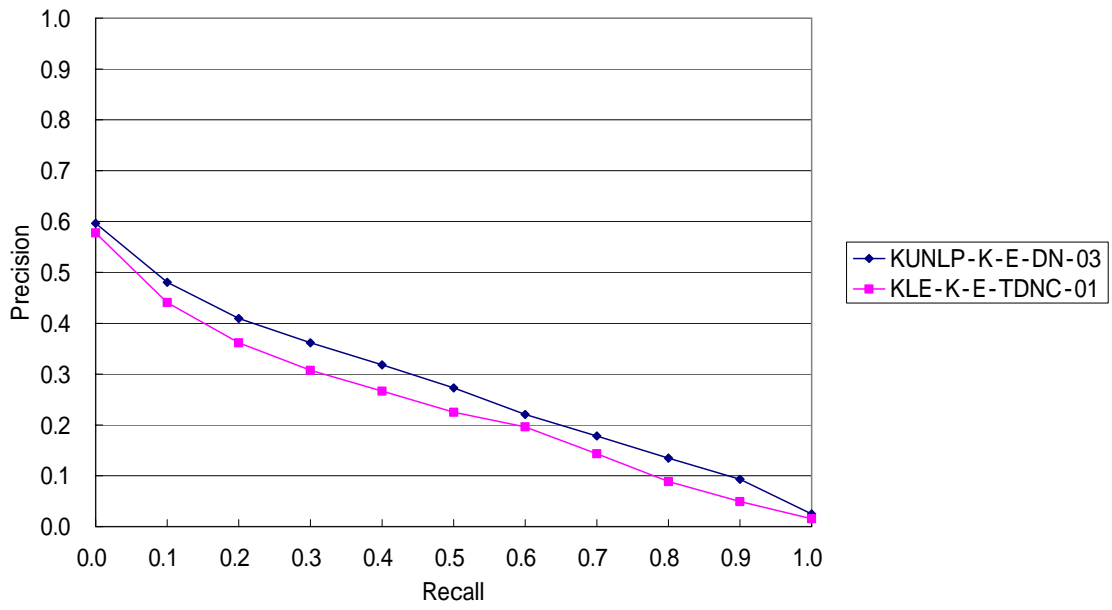
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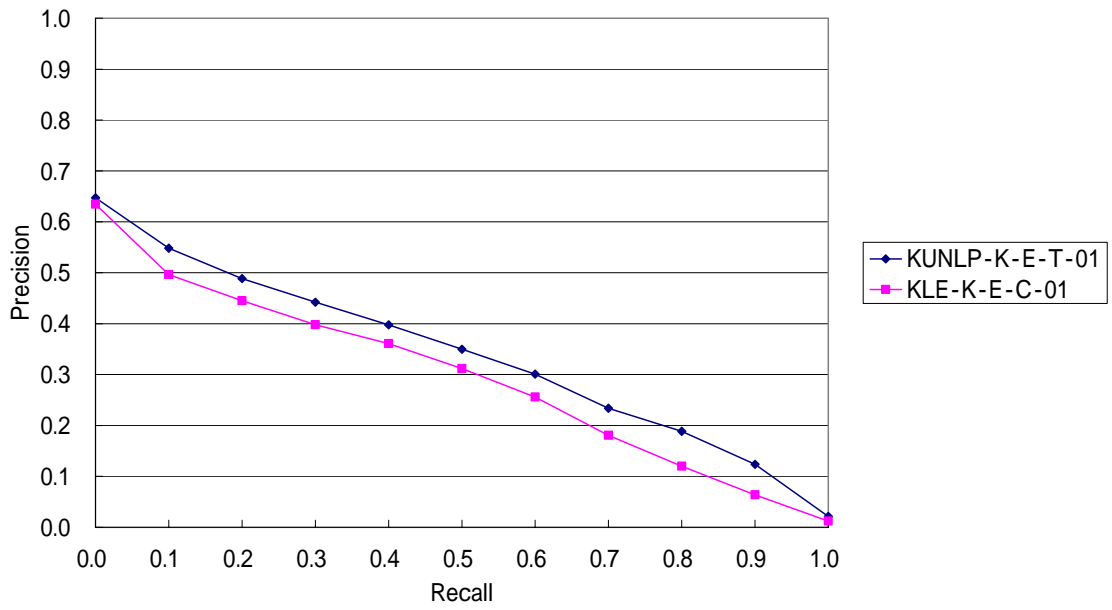
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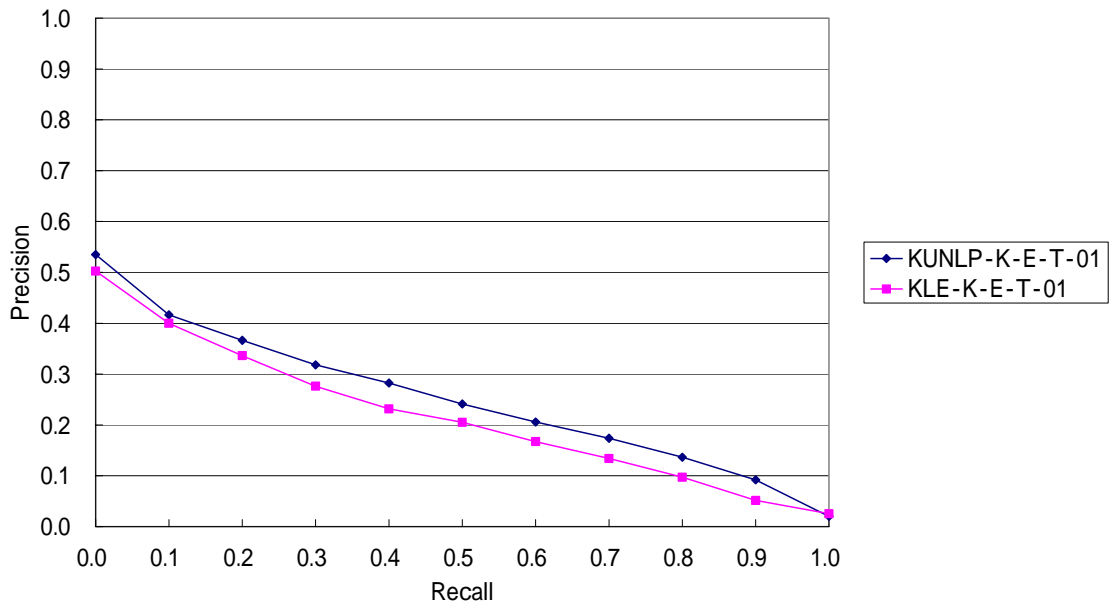
K-E(Rigid)



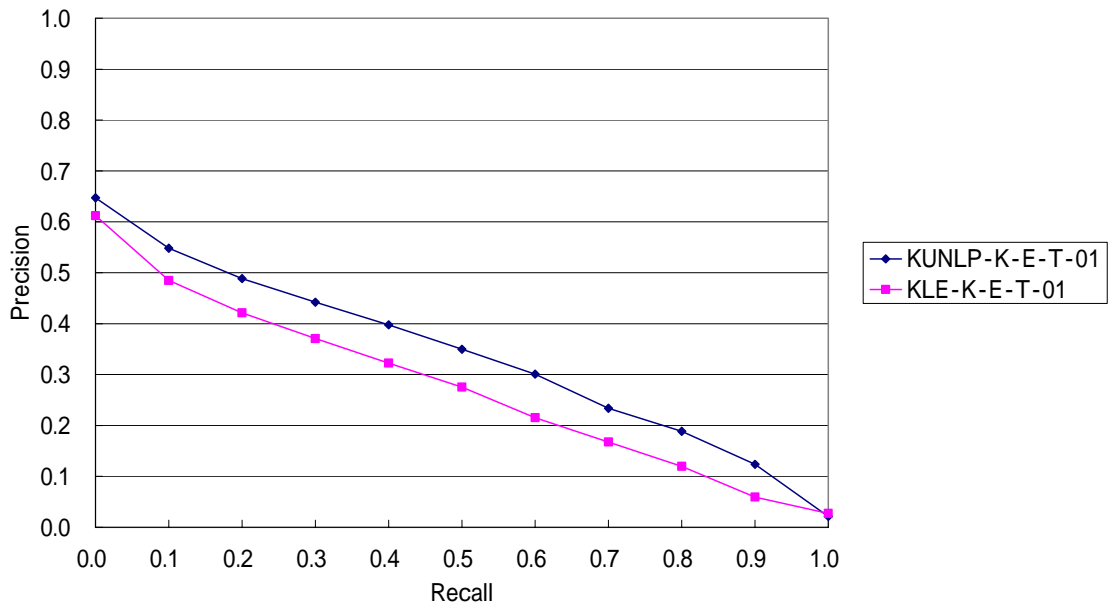
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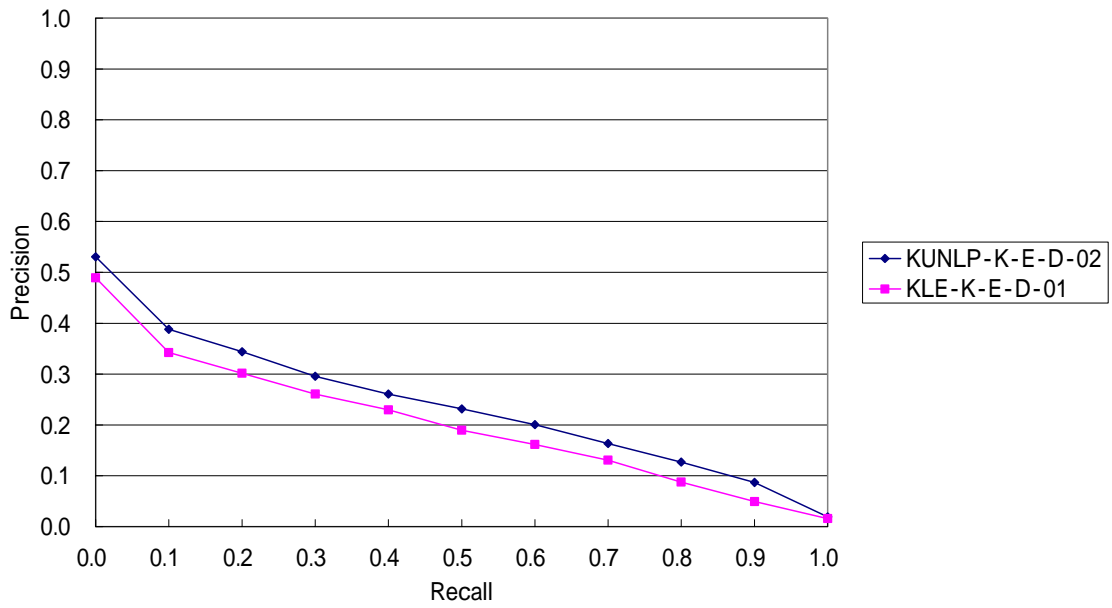
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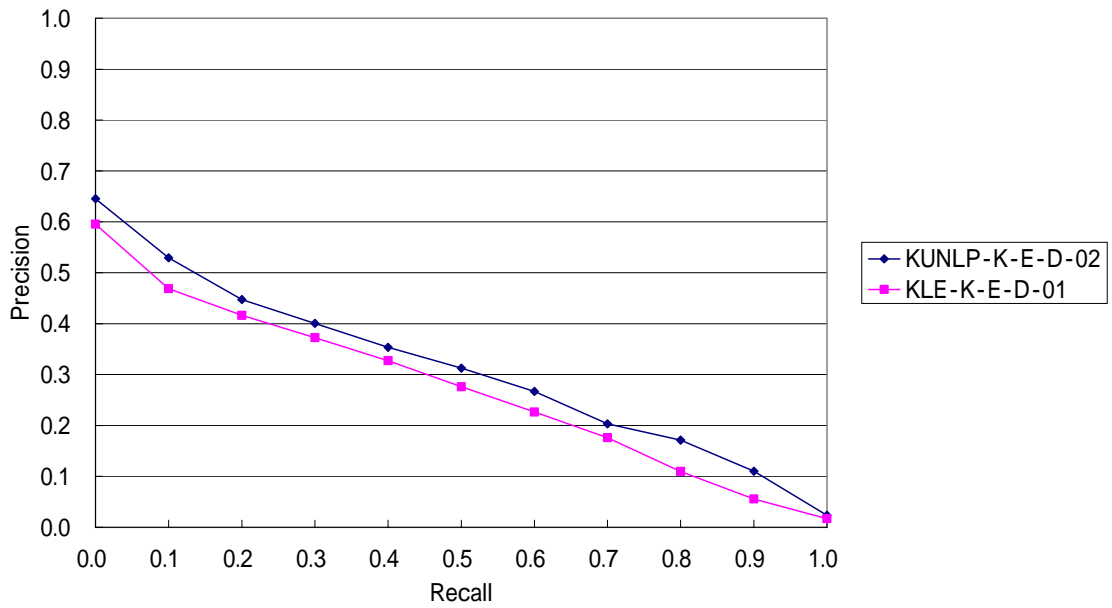
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K-E-D(Rigid)

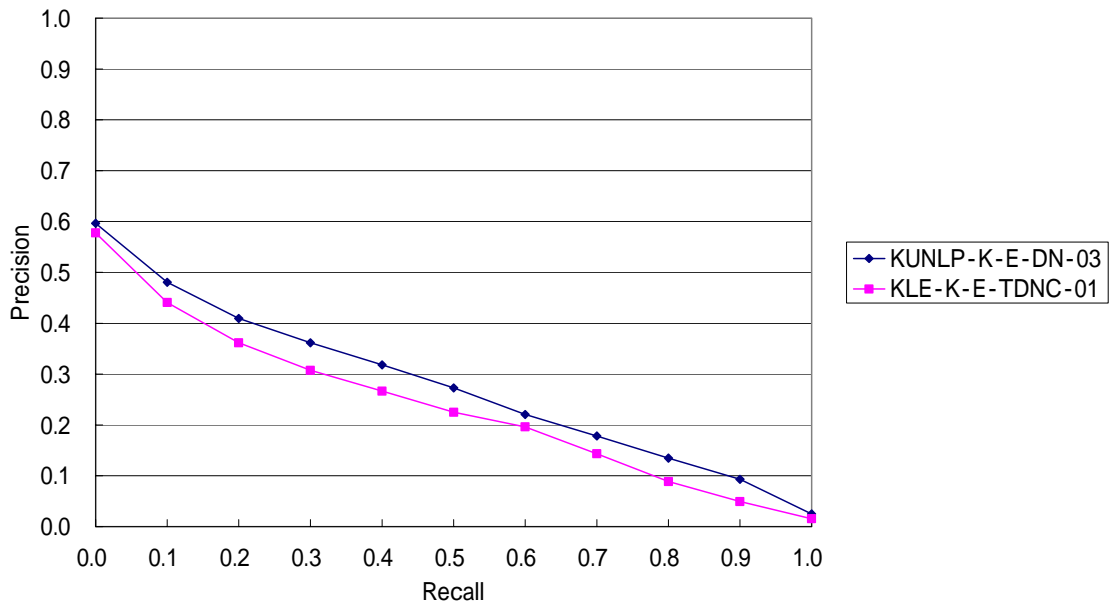


K-E-D(Relax)

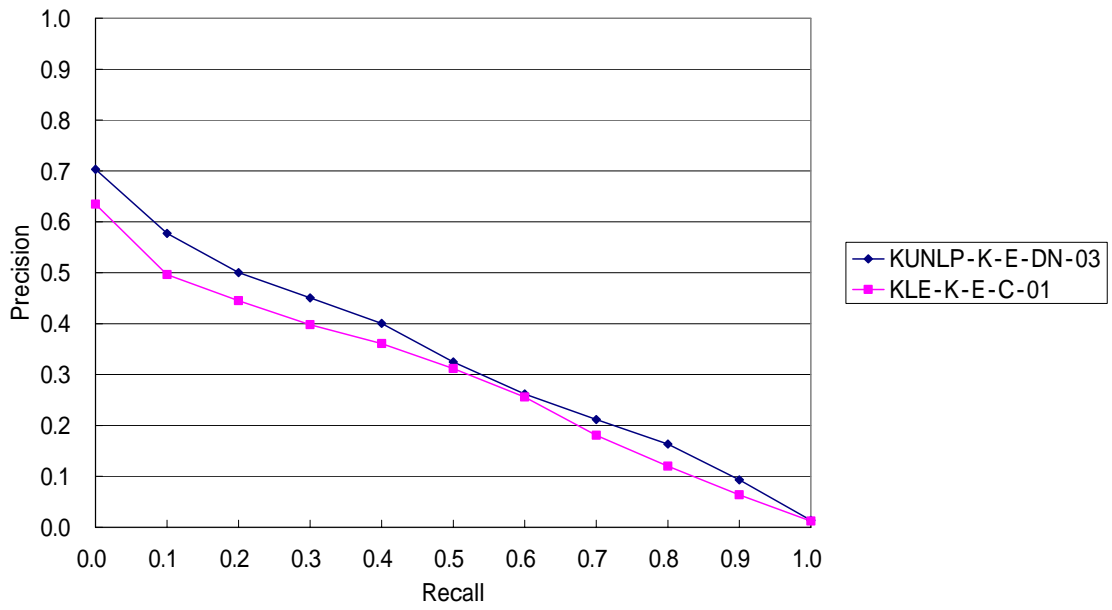




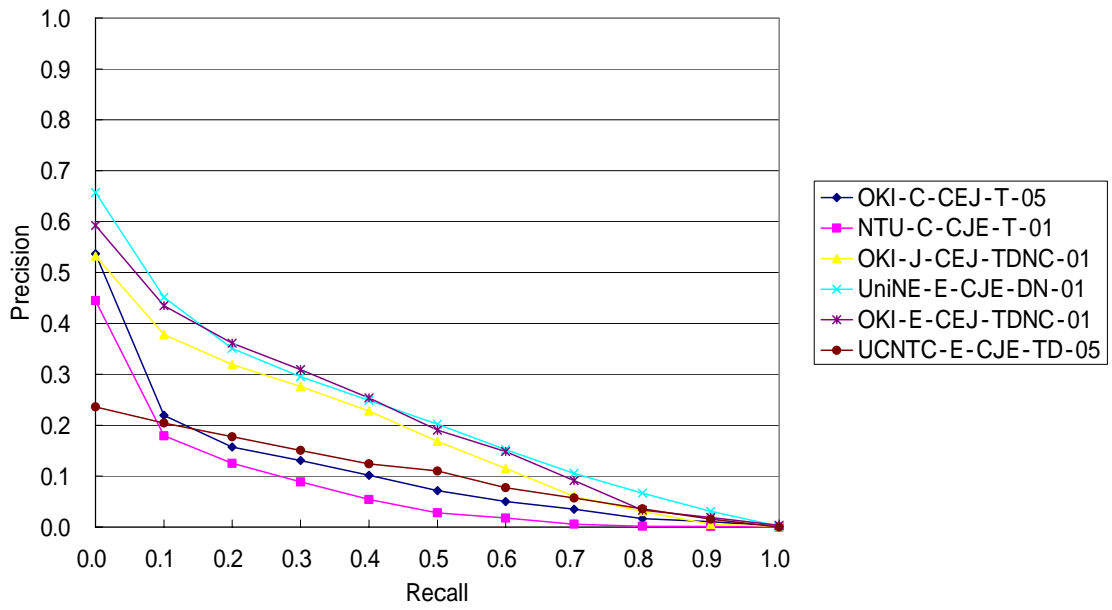
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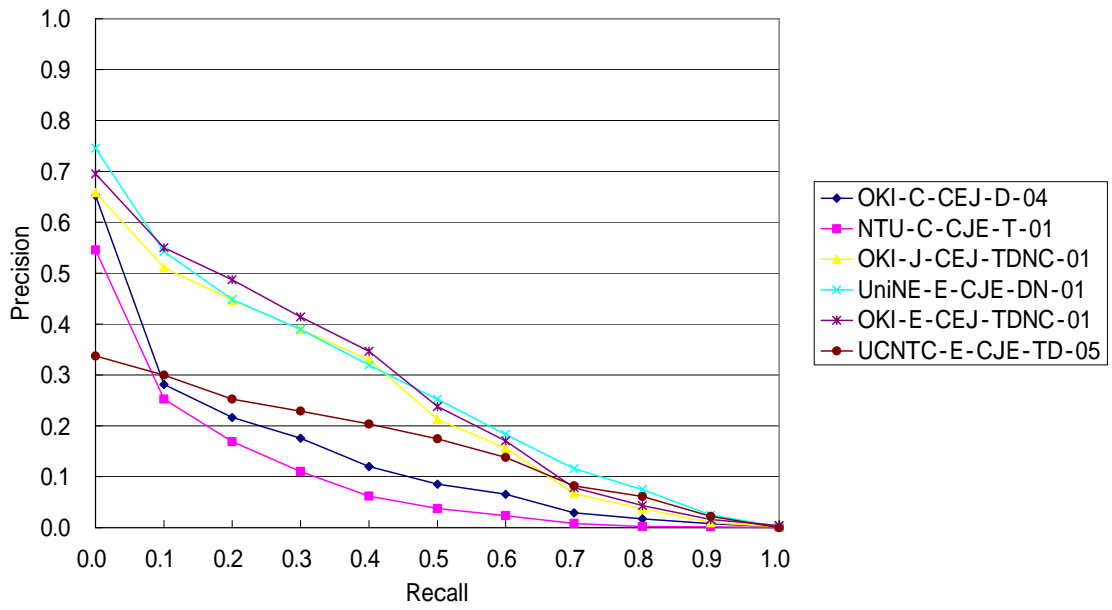
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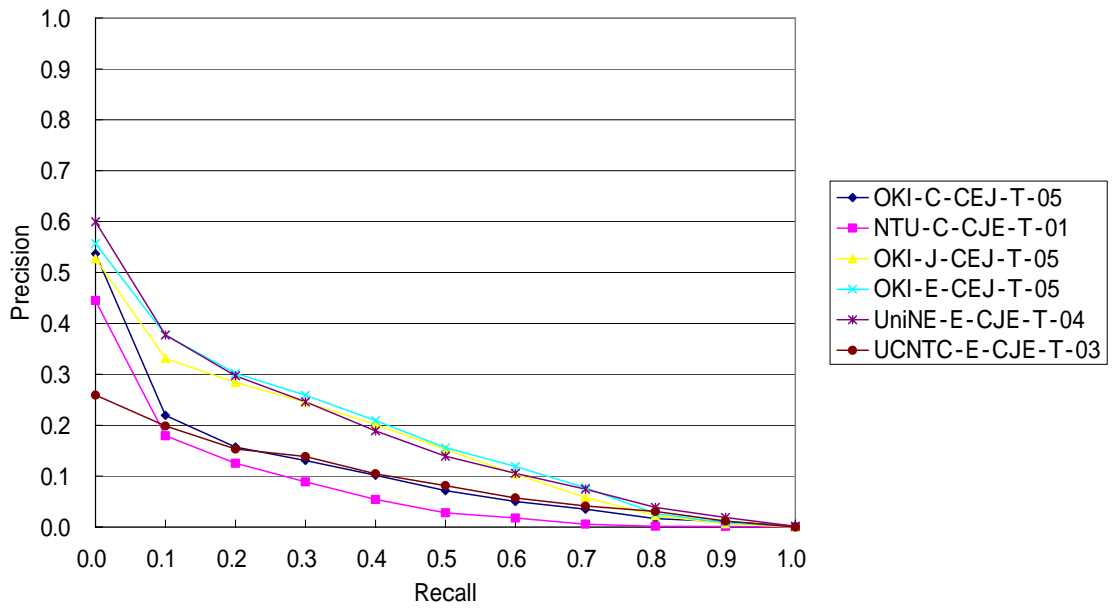
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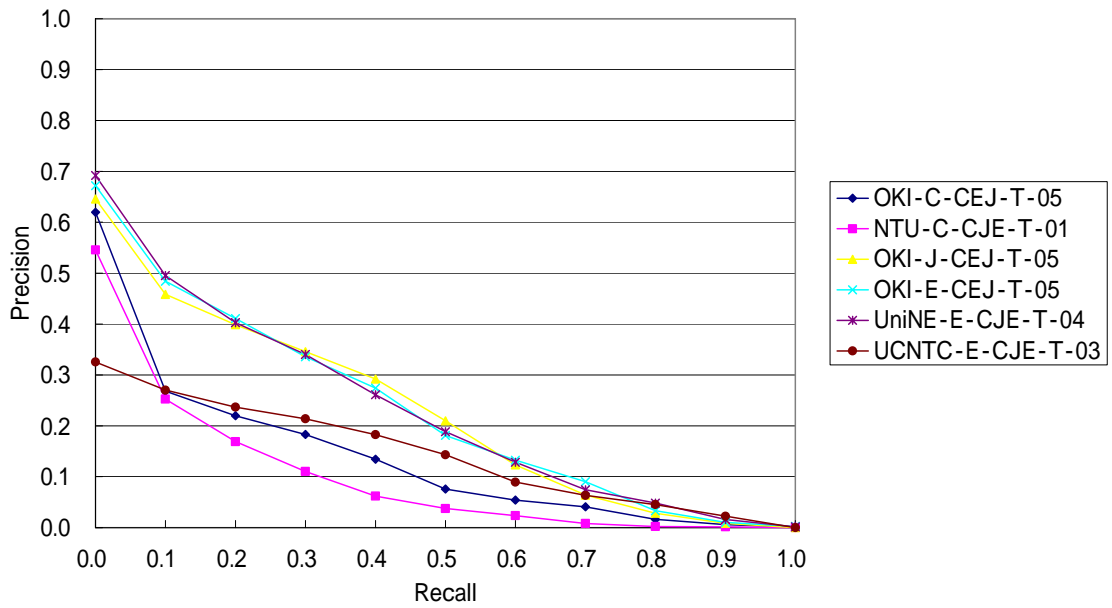
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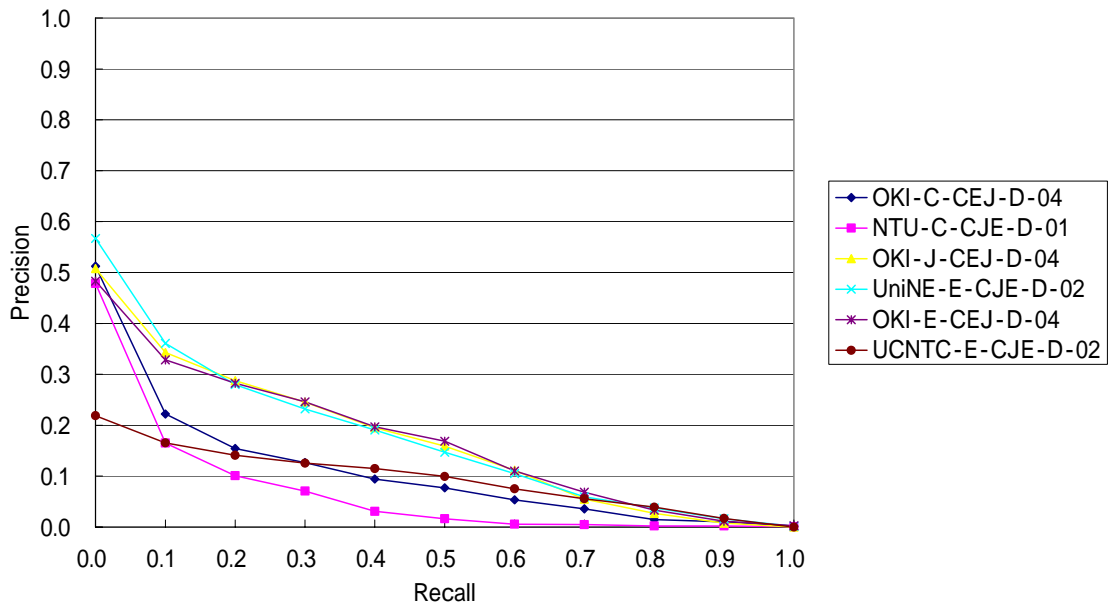
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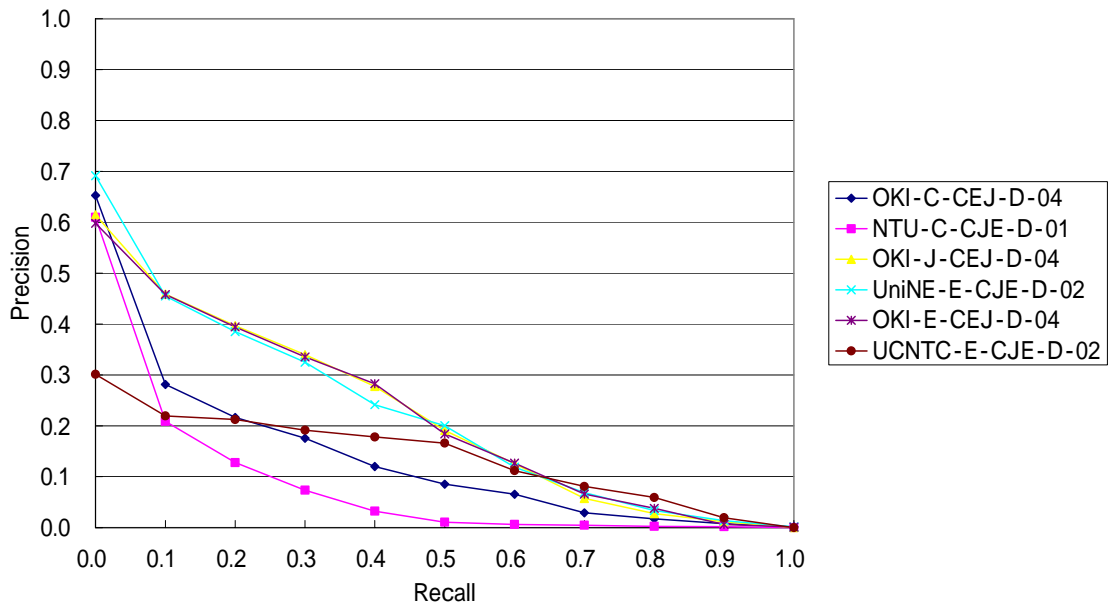
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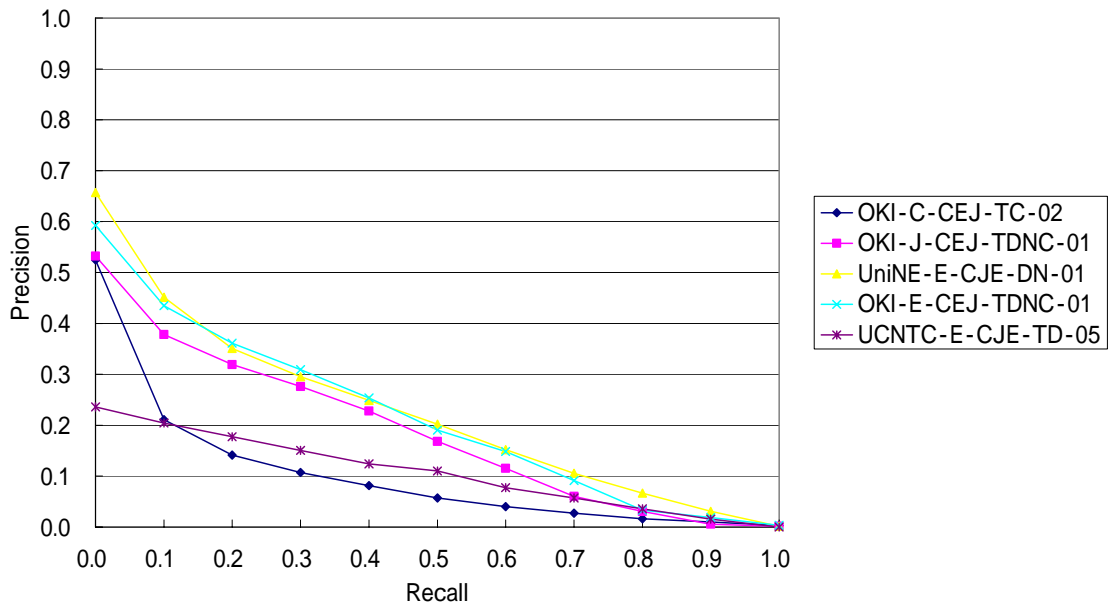
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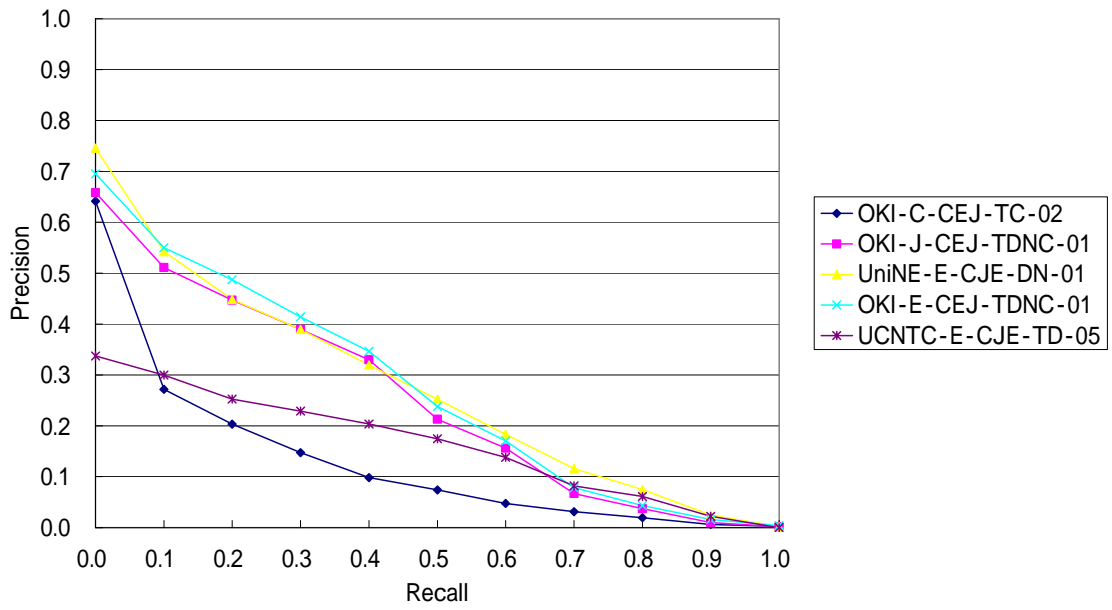
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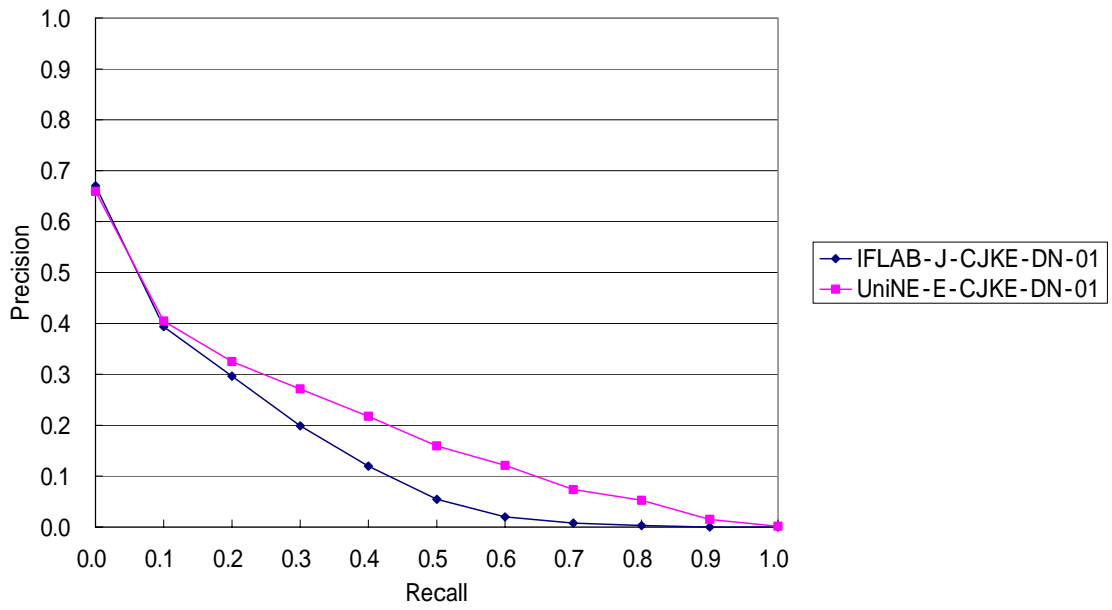
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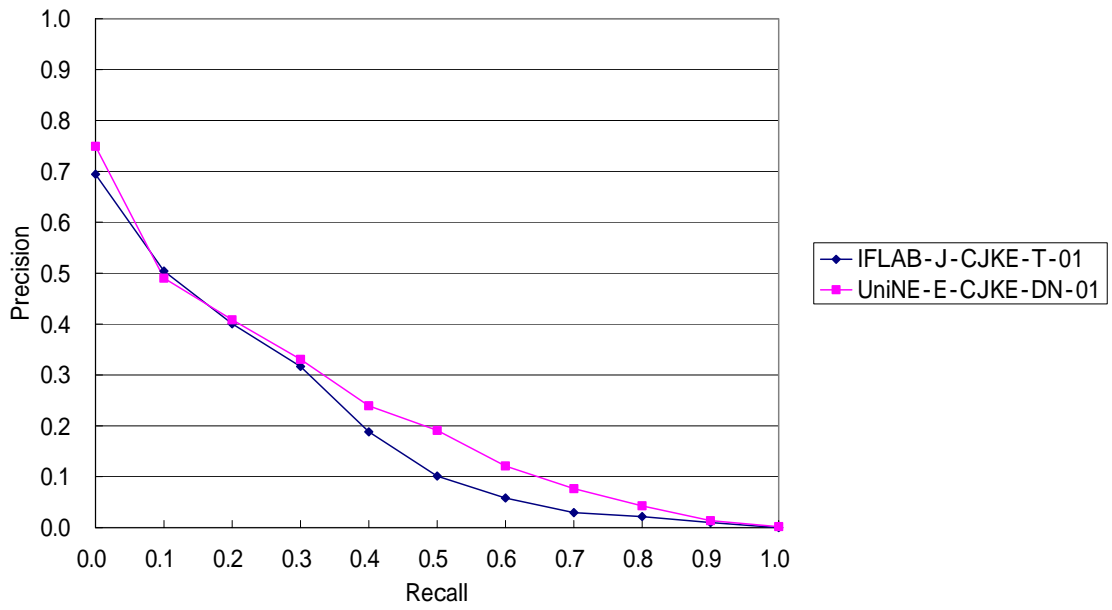
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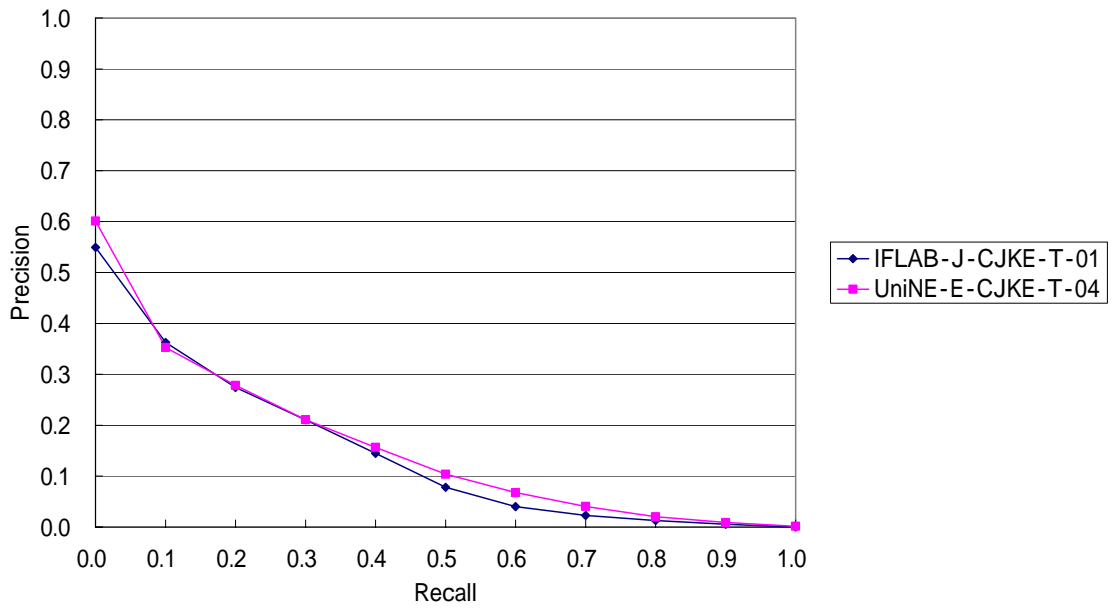
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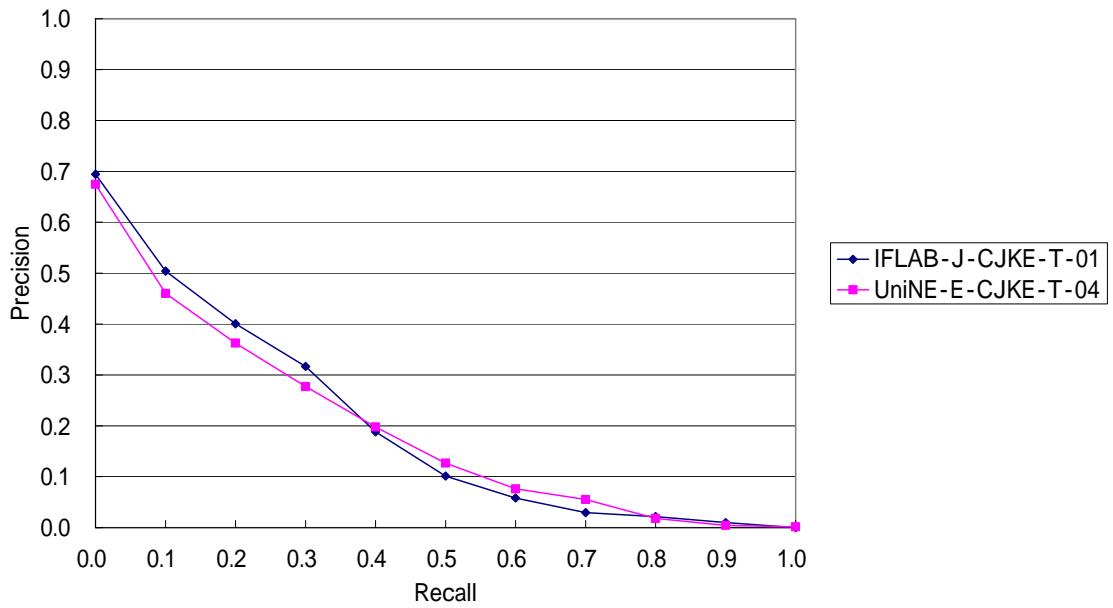
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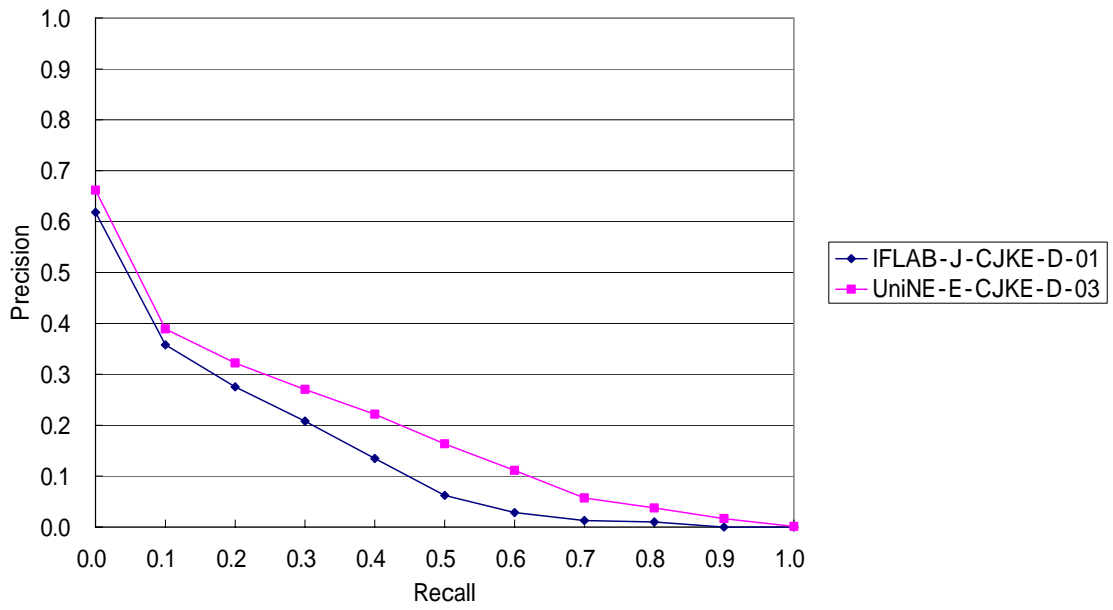
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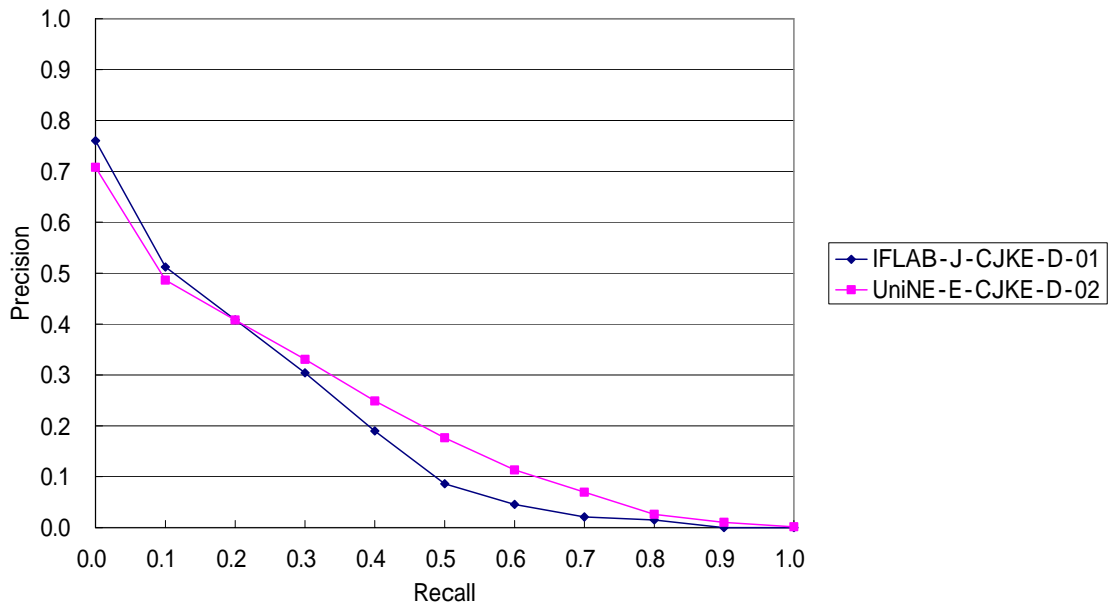
X-CJKE-T(Relax)



X-CJKE-D(Rigid)

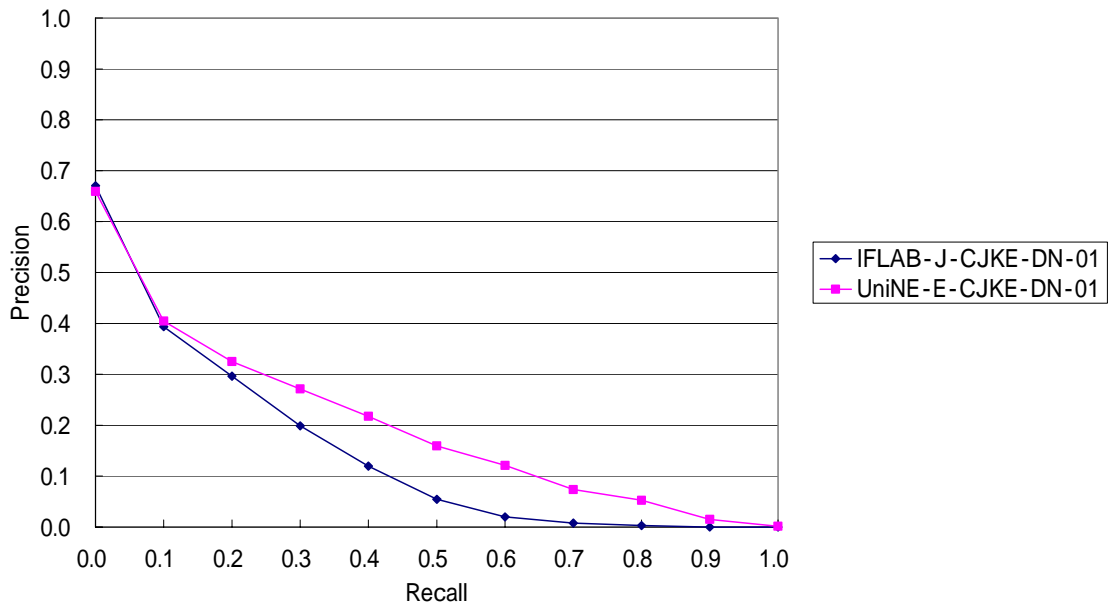


X-CJKE-D(Relax)





X-CJKE-O(Rigid)



X-CJKE-O(Relax)

