Low Cost Evaluation for Diversity and Novelty

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Outline

- Background
- Motivation
- Preliminary Results
- Related Work
- Our Method
- Next Steps

Background:
Diversity and Novelty Evaluation

TREC Diversity and Novelty Example

Query: No. 196 from WT2012

Query: sore throat
Subtopic 1: What causes a sore throat?
Subtopic 2: Find home remedies for a sore throat.
Subtopic 3: Find information on throat cancer.
Subtopic 4: What does it mean when my throat is sore on only one side?

Manual Label Example

Query-id	Subtopic	Docid	Label
196	1	clueweb09-enwp02-06-01125	1
196	2	clueweb09-enwp02-06-01125	0
196	3	clueweb09-enwp02-06-01125	1
196	4	clueweb09-enwp02-06-01125	0
……			

Diversity and Novelty Measure Example: ERR-IA

$$ERR-IA = \sum_{top-k} \frac{1}{k} \sum_{subtopic\ i} g_{k,i}\,(1-\alpha)^{c(k,i)}$$

$g_{k,i}$: relevance labels for the k-th document on subtopic i

$c(k,i)$: the count of relevant documents for subtopic i before the k-th document

α : the parameter for penalizing the repeating subtopics, normally set as 0.5

- **Apart from ERR-IA, α-nDCG and NRBP are also popular measures.**
- **Their definition is directly based on the relevance labels, thus the evaluation quality highly depends on the labels.**

Datasets

Document Collections

- ClueWeb09 Category A (CwA): **500 M English web pages**
- ClueWeb09 Category B (CwB): **50 M English web pages**
- Constructed Dataset (CwC): **450 M web pages from CwA but not in CwB**

Query Sets and Labels

- TREC Web Track (WT) 2009-2012, 200 queries with their labeled documents
- Runs for evaluation: 48 for 2009, 32 for 2010, 62 for 2011, and 48 for 2012

Objective

- Reconstruct the ranking of runs according to ERR-IA with incomplete judgments
- Kendall's τ is used to measure the correlation among rankings
- Kendall's τ: scaled between -1 and 1

$$\tau = \frac{(Number\ of\ Concordant\ Pairs) - (Number\ of\ Discordant\ Pairs)}{Total\ Number\ of\ Pair\ Combinations}$$

Motivation:

Towards Lost Cost Evaluation

Cost of Evaluation

- Top-k pooling: collect top-k from all candidate runs to generate a pool
- Manually label every subtopic document pair in the pool
- Limit to shallow pooling depth, e.g., top-25

Year	#Query	#Systems	Pooling size	#Total labeled doc	#Labeled Relevant doc
2009	50	48	20	24,817	4,942
2010	50	32	20	15,352	6,553
2011	50	62	25	19,344	5,030
2012	50	48	20/30	16,036	5,559

Low Cost Evaluation Framework

Three Components in Evaluation:

Test Query Set

Document Collections

Manual Labeling

Selects fewer candidate documents to label

- **Better discriminating ability**, e.g., only few systems can return a certain relevant document
- **Based on document content**, e.g., centroid documents in the similarity space are more representative
- **Combine the above two methods**

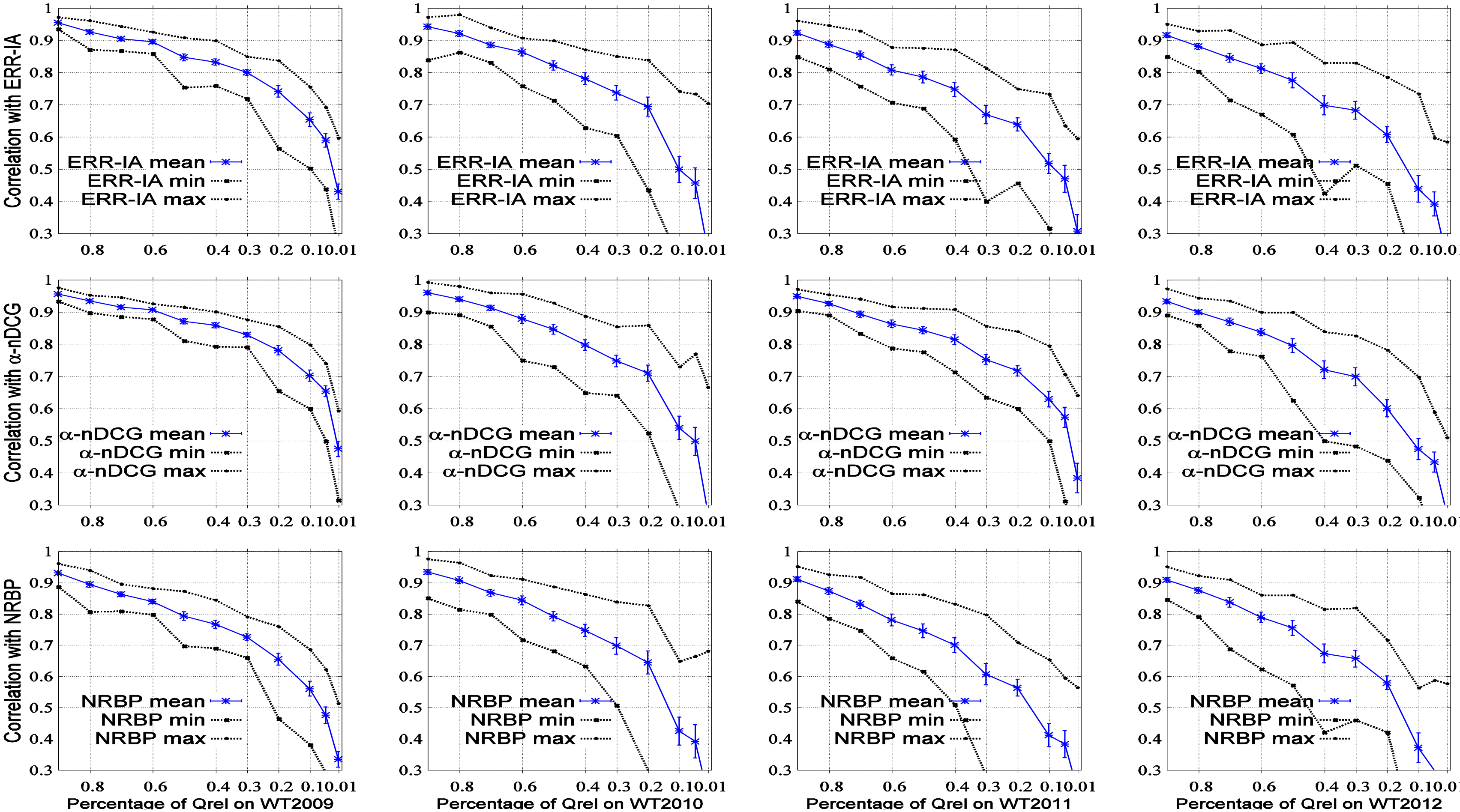
Reuses existing labels.

- **Regard unlabeled as irrelevant**
- **Remove unlabeled documents**
- **Predict labels for the unlabeled documents**

Preliminary Results:

Label Fewer Documents & Reuse the Labels

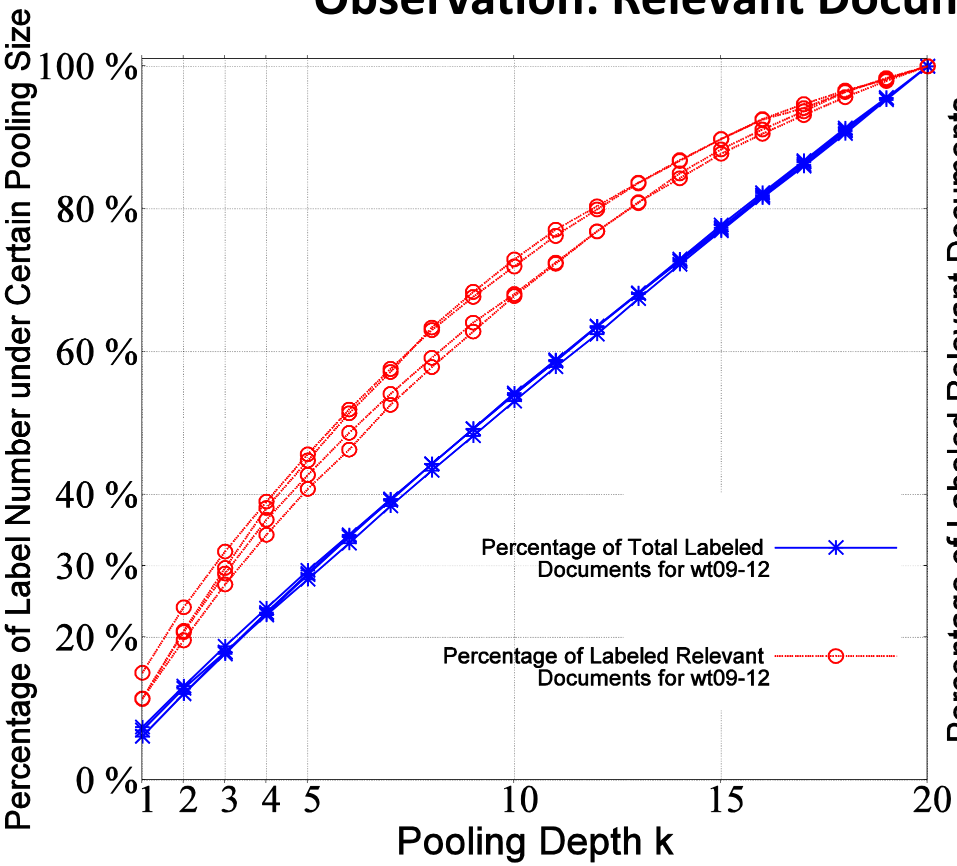
Randomly Select Fewer Documents to Label

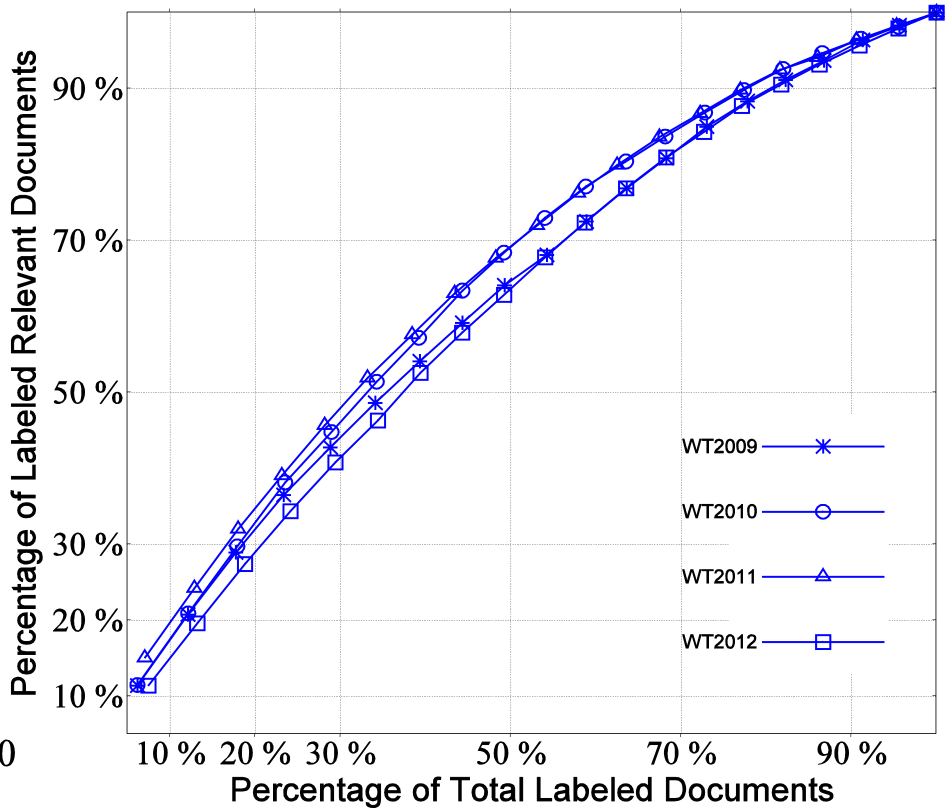


- Percentage of available labels with random sampling versus the Kendall's tau correlation, repeating 30 times: **evaluation with 60% of labels is not reliable**
- Lost cost evaluation can't be realized by simply random sampling, and the evaluation is sensitive to the completeness of the labels

How to Select?

Observation: Relevant Documents Distribute not Uniformly

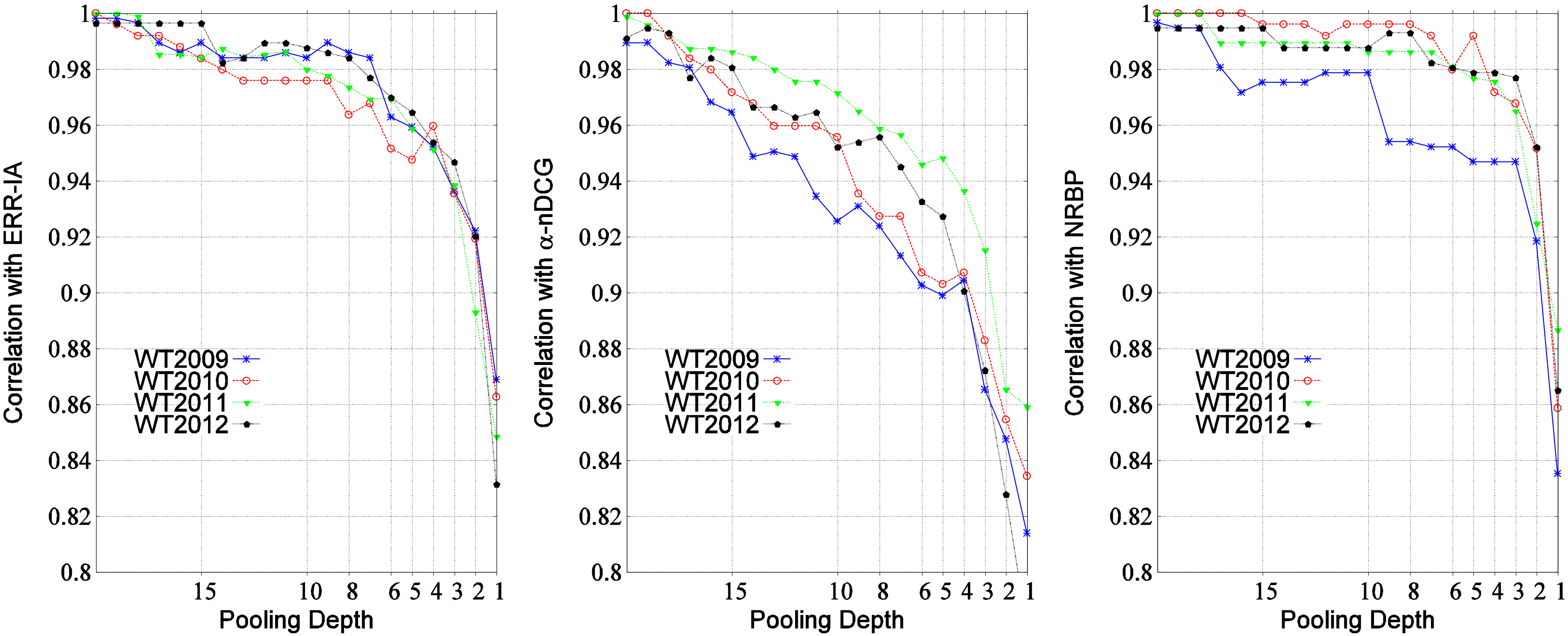




- Left: percentage of relevant (red) / total (blue) w.r.t. the pooling depth
- Right: percentage of total labels w.r.t. the relevant labels
- **Relevant documents distribute not uniformly on the pooling depth, i.e., shallow pool contain larger portion of the relevant documents**

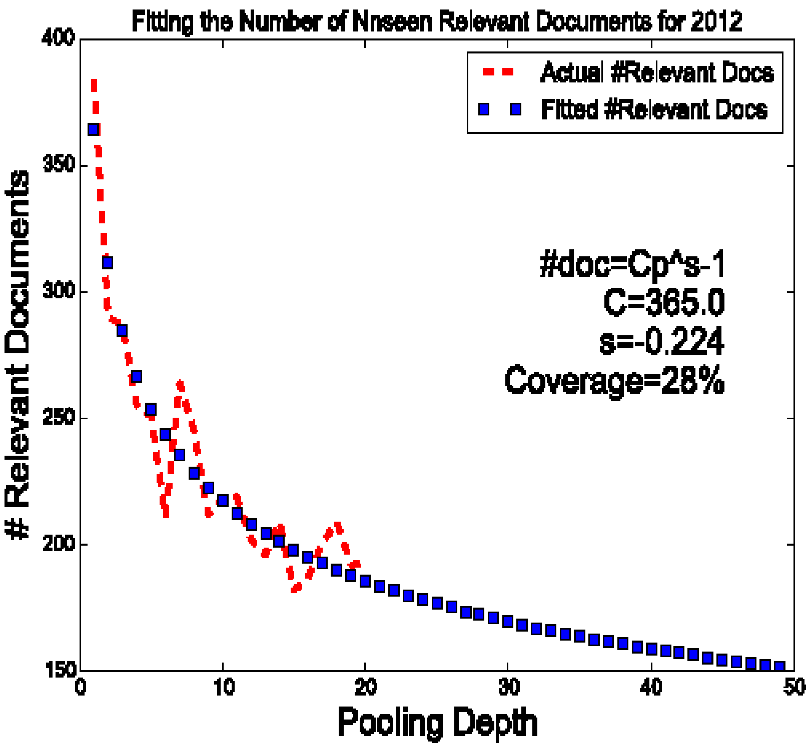
Select According to the Rank from Rival Systems

Preliminary Results: Labels on Shallow Pool Simulate Complete Evaluation Perfectly



- Kendall's tau correlation between the ranking determined by full judgment w.r.t. the judgment on different pooling depth, for measures ERR-IA, α-nDCG and the NRBP
- **Label on top-6 pool (40% of total label) is enough to get over 0.9 correlation w.r.t. complete judgment**
- We can also use document content or discriminating ability etc.

Difficulties in Reusing the Labels: Unlabeled Documents



X-axis: Pooling Depth

Y-axis: Number of new relevant documents

How many do we miss? (Zobel, 98)

- Count the number of new relevant documents in pool@i given labeled pool@i-1
- Fit the curve for existing pool and predict for deeper pool, e.g., pool@100
- Pool@20 covers 25% - 30% relevant documents
- Unlabeled relevant documents are due to their low rank, e.g., rank at 50

Why do the unlabeled documents exist?

- Incomplete coverage of the relevant documents in existing judged pool.

Existence of the Unlabeled Documents: Predict the Labels

When might they exist?

- When evaluates systems not included in the pooling
- On a new document collection
- When going deeper than the pooling depth, e.g., ERR-IA@30

Why are they problematic?

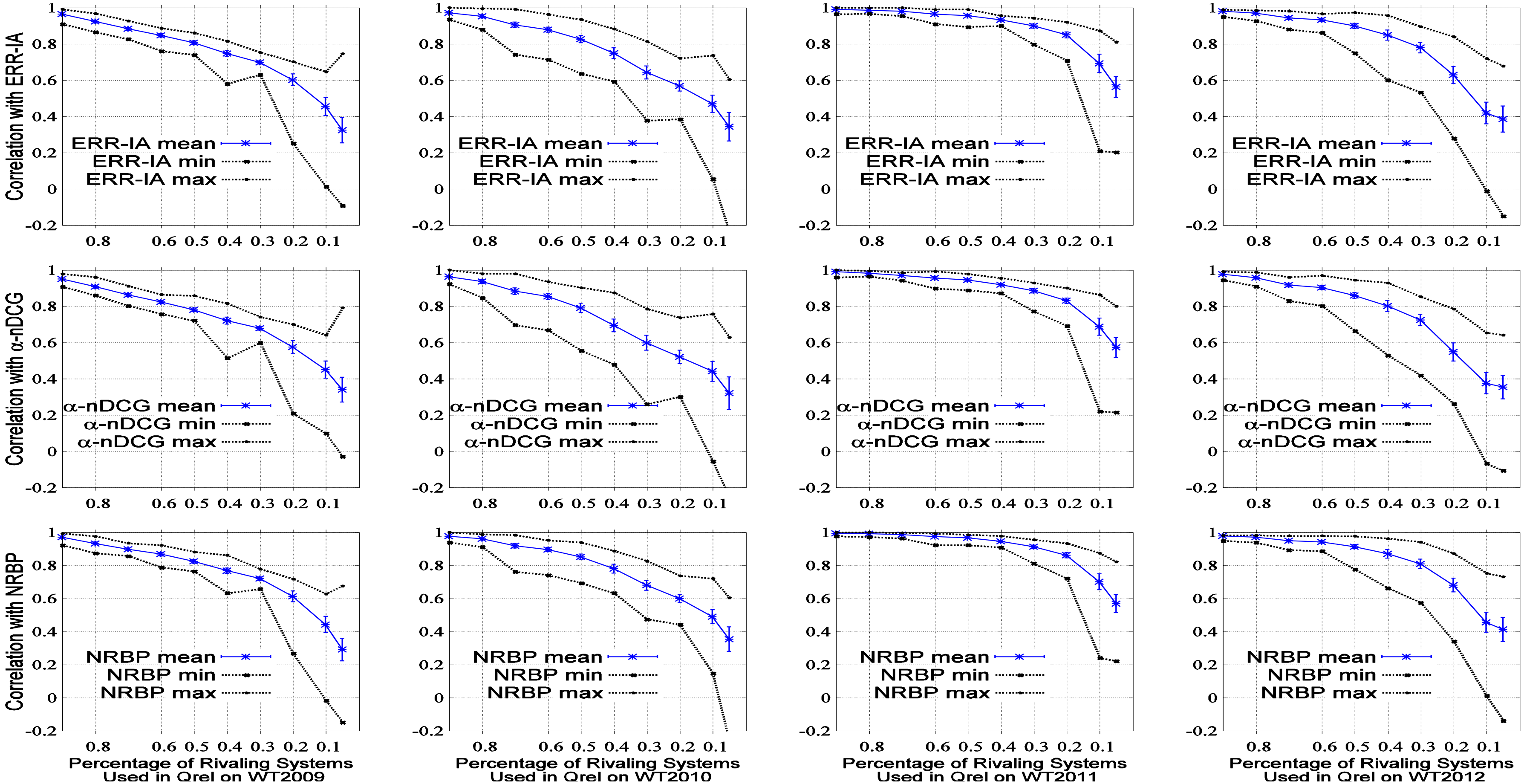
- Direct dependence on the labels, e.g., ERR-IA
- Missing labels have to be mitigated before evaluation

How to deal with them?

- Regard unlabeled as irrelevant: underestimates (Sakai et.al, 12)
- Remove unlabeled documents (condensed list): overestimate (Sakai et.al, 12)
- Predict the labels for unseen documents (Büttcher et.al, 07)(Carterette & Allan, 07)

Reuse the Existing Labels

Leave N Out: Evaluate Systems without Contribution to the Pool



- Percentage of certain percentage of systems versus the Kendall's tau correlation, repeating 30 times: evaluation with less than 50%-60% systems contributing labels is not reliable
- **The existing measurement is not reusable, being biased towards systems without contributions to the pool**

Brief Review of Related Works

Related Work for Low Cost Evaluation

- **Sample documents to be labeled:**

  Identify the crucial documents to label by selecting documents with best discriminating ability, like MTC. (Carterette et. al, 06)

- **Learning to predict the missing labels**

  Mitigate the missing labels by predicting labels. Only has been tested for mitigating small portion of missing labels on adhoc task.
  (Büttcher , 07) (Carterette & Allan, 07)

- **Condensed list of relevance judgment**

  Remove all the unjudged documents instead of regarding them as irrelevant, tend to over-estimate the unlabeled systems. (Sakai, 13)

- **Reduces query numbers:**

  Use fewer queries for testing and conclude statistical significant result. Most are retrospective method, the performance is unclear. (Robertson, 11)

Our Works on Reusable Evaluation:

Results for Pointwise Prediction & Listwise Prediction

Mitigate the Unlabeled Documents:
Predict the Missing Labels

Given query, subtopics, and top-k documents to evaluate.

Options for prediction:

- **Pointwise prediction** (Büttcher et.al 07) (Carterette & Allan, 07)

<query, subtopic, doc>: <relevant, irrelevant>

- Pairwise prediction (A promising method, future work):

1) <query, doc_1>: <relevant, irrelevant>
   <query, doc_2>: <relevant, irrelevant>
1) <query, subtopics, doc_1, doc_2 >: <same subtopic, different subtopics>

- Listwise prediction

<query, subtopics, top-k docs>: the diversity and relevance of top-k docs

Results for Pointwise Prediction

Predict Labels for Document Subtopic Pair

Prediction Setting

- Given information of query, subtopic and the tf-idf for each documents
- Select terms with the decreasing order of the collection frequency
- Similar setting with (Büttcher et.al 07)

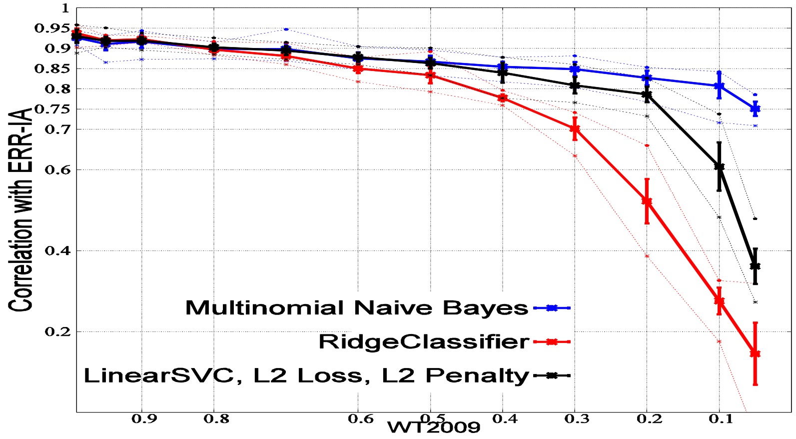
Learning Tools

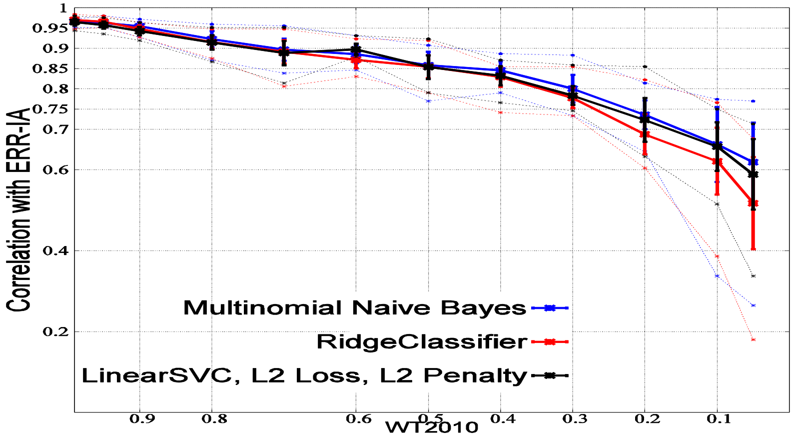
- Scikit package based on python (http://scikit-learn.org/)
- Use Naïve Bayern, Linear Regression and the SVM to train
- With default setting of the parameters from the toolkit

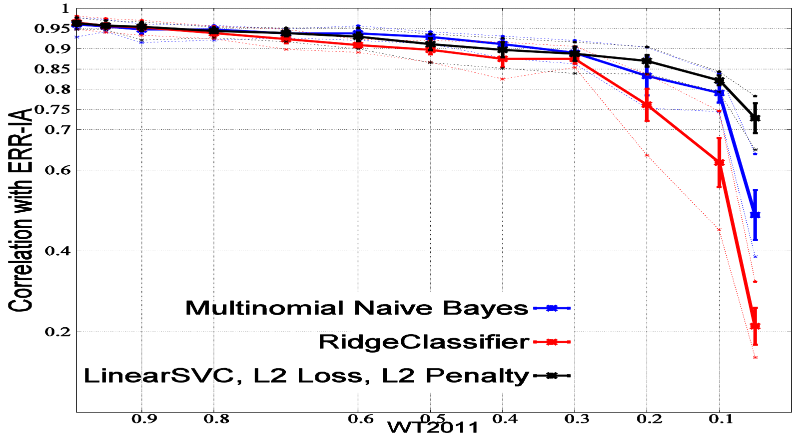
Performance

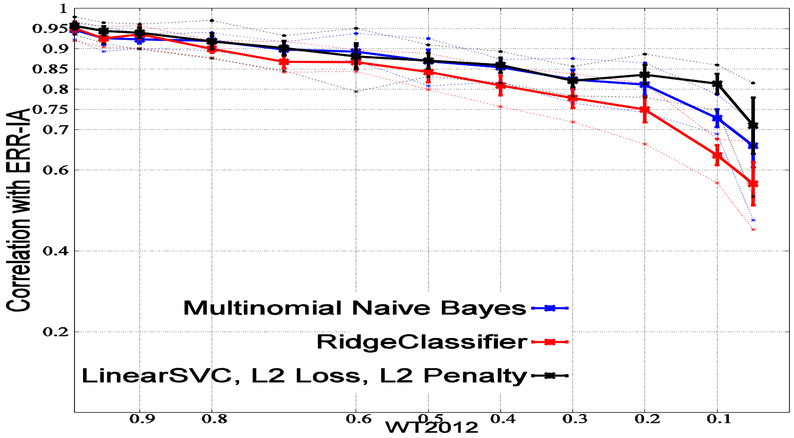
- Partially mitigate the missing labels, can reconstruct the ranking of systems with as less as 40%-50% available labels
- ? Why we need listwise prediction…….

Evaluation on Randomly Selected Fewer Labels









- Percentage of available labels with random sampling versus the Kendall's tau correlation, repeating 6 times: **evaluation with 40%-50% of labels is not reliable**
- Pointwise prediction can partially mitigate the missing labels

Listwise Prediction
Reusable Measure Framework & Current Method

Generate subtopic distributions

Given query and its t subtopics:
Merge all corresponding relevant documents to generate the LM for each subtopic.

Compute distance matrix against the subtopic distributions

Given top-k documents to evaluate
Compute KL-divergence at each position i, e.g., top-i, and for each subtopic. Get a $k \times t$ distance matrix.

Compute measure based on the distance matrix

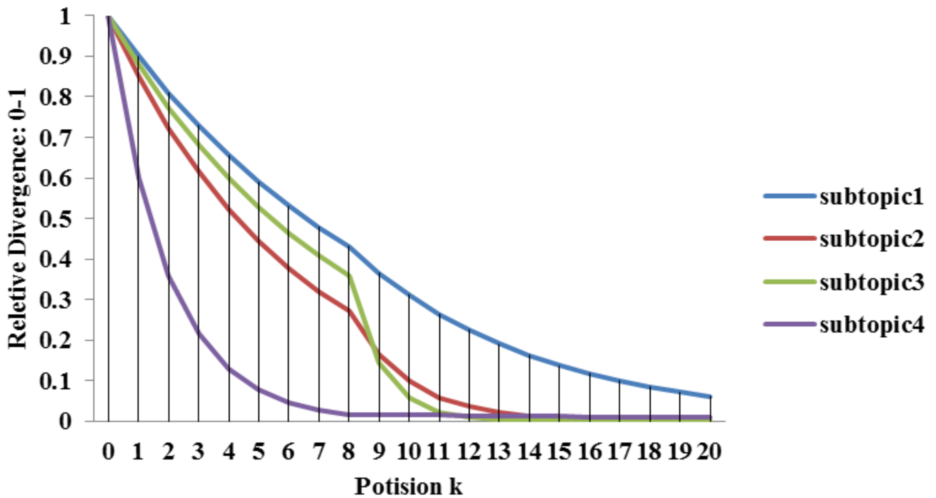
Given distance matrix:
Summarize the distance matrix $D_{k,t}$ with simple function, i.e., Abs and Delta.

Listwise Prediction

Describe the Shift & Map the Shift to Measure

- **KL-divergence**. On each subtopic i, compute the divergence between the subtopic LM i and the top-k LM at each position k, computing the divergence matrix to describe the shift procedure

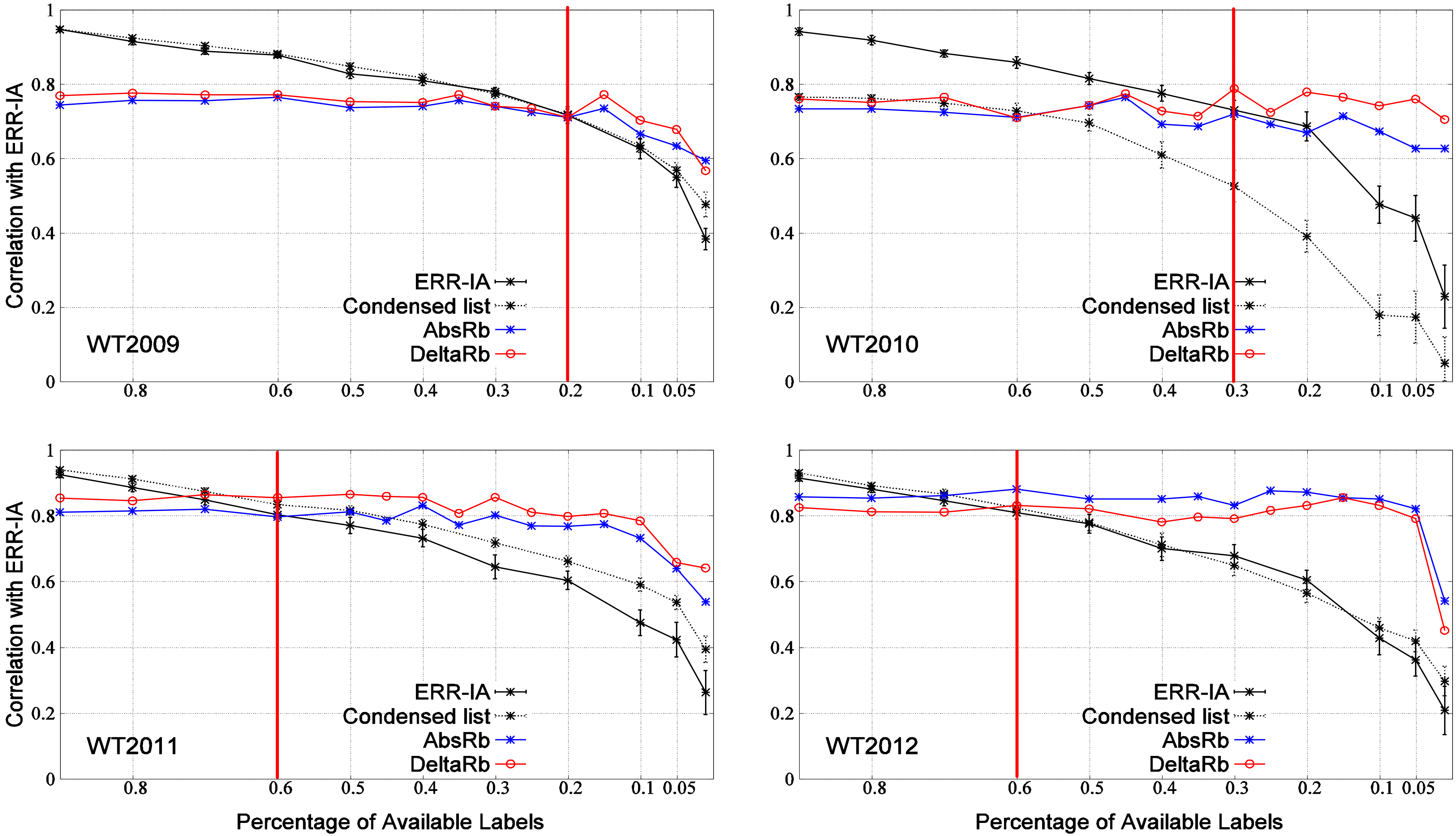
$$KLD(\Theta_{q_i} \parallel \Theta_{R_k}) = \sum_{v \in \mathcal{V}} P[v|\Theta_{q_i}] \log \left(\frac{P[v|\Theta_{q_i}]}{P[v|\Theta_{R_k}]} \right)$$



- Other options to replace $distance(top-k, t-th\ subtopic)$: use the probability to compute the $D_{k,t}$
- Final step: map each $D_{k,t}$ to a effective measure, i.e., a real value

Evaluation: Robustness with Incomplete Labels

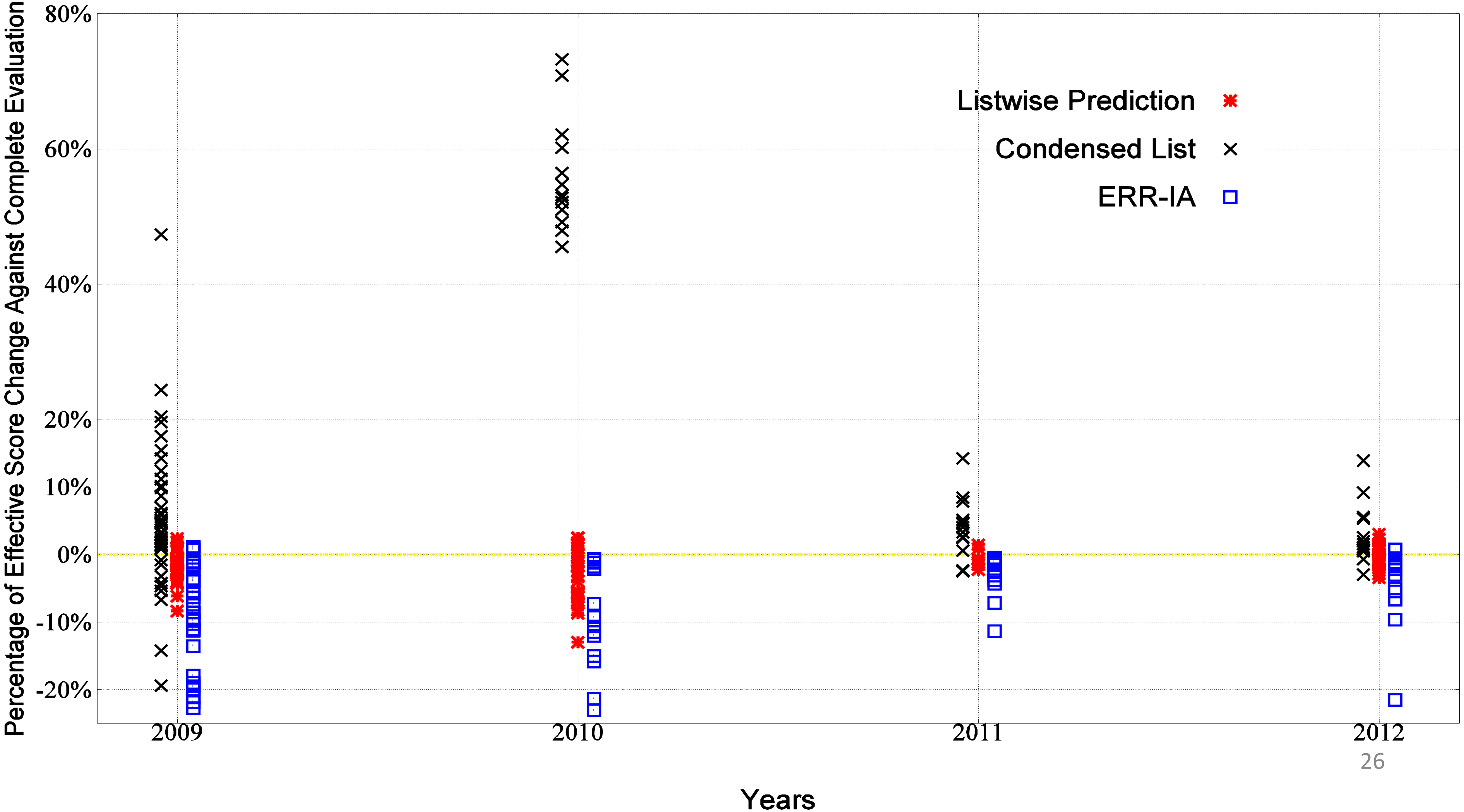
Percentage of Available Labels VS Correlation for 4 years



X-axis: Percentage of labels **Y-axis:** Correlation against system ranking with complete labels

Evaluation: Reuse Labels to Evaluate Unlabeled System

- **Leave One Run Out (LORO):** given N runs, gather labels from N-1 runs, regard the remaining run as missing run
- **Measure Difference:** compute the difference of ERR-IA score of the missing run on complete and LORO judgments
- **Overestimate & Underestimate:** the near zero difference indicates the measure has no bias in evaluating unlabeled run



Evaluation: Reuse Labels on New Document Collection

Kendall's τ Correlation with Label Based Measures

		AbsNb	AbsRb	DeltaNb	DeltaRb
2009	α-nDCG	.72	.70	.73	.69
	ERR-IA	.78	.78	.76	.76
	NRBP	.74	.74	.70	.74
2010	α-nDCG	.72	.66	.74	.76
	ERR-IA	.70	.66	.72	.75
	NRBP	.68	.65	.71	.73
2011	α-nDCG	.71	.76	.79	**.81**
	ERR-IA	.67	.75	.73	**.81**
	NRBP	.64	.74	.69	.79
2012	α-nDCG	.23	.40	.31	.51
	ERR-IA	.26	.44	.31	.54
	NRBP	.26	.45	.31	.54

Generate subtopic distribution on CWB and evaluate runs on CWC

Next Steps:

- **Reusable Evaluation**
- **Select Documents to Label**

Future Works in Low Cost Evaluation

Reusable Evaluation:

- Generation of subtopic distribution: text summarization, snippet generation etc..
- Regression: from distance matrix to the value of effectiveness measure
$$Measure\ Score = f(Abs, Delta)$$
- Pairwise/Pointwise prediction to predict the missing labels

Select Documents to Label:

- Select documents combining the discriminating ability of the documents and of the document content

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Q & A