

Statistical Evaluation of Information Distillation Systems

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Overview

- Information distillation
- Evaluation objectives
- Data analysis and statistical methodology
- Simple examples

Information distillation

Text & Audio Sources

Structured

News wire
Radio/TV news

Unstructured

Chat rooms
TV talk shows

English

Arabic

Mandarin

Information Distiller

- Document retrieval
- Transcription / Translation
- Relevance filtering
- Redundancy filtering

English Response Text

English Query Text

- English queries produce English response texts, even with foreign text/audio sources

Acknowledgement

- Our evaluation methodology was developed for the GALE program (Global Autonomous Language Exploitation) under DARPA/IPTO support
- Our methodology may be used for other evaluations that share similar objectives
 - Evaluate unstructured response texts for information content
 - Penalize responses for irrelevance, redundancy, and missing information
 - Provide comprehensive statistical performance metrics (recall, precision, F-value, proficiency, ...)

System evaluation scope

- Our methodology focuses on overall *system* performance – not component performance
 - We evaluate the distiller response for relevance to the input query
 - The performance evaluation penalizes redundant, missing, and irrelevant information, as well as any gibberish in the response
 - We don't use transcription and translation metrics, but such errors reduce the system-level performance that we do measure
- This presentation doesn't describe our methodology for evaluating document citations
- Nor does this presentation address usability, readability, or utility metrics

Technical approach

- Annotators divide the distiller's relevant response text into *information nuggets* and group these into *nugs*
 - *Nugs* are fuzzy sets of more-or-less equivalent nuggets
 - The *nuggets* are manually identified by annotators in GALE
 - In principle, nuggets may be automatically parsed
- Annotators analyze the information content of the nuggets for relevance to the query
- Annotation tasks include
 - Grouping nuggets into nugs based on their meanings
 - Assigning *Relevance weights* to the nugs
 - Assigning *Degrees of membership* to relatively imprecise nuggets that overlap more specific nuggets in meaning

Nug 1

- Query: How are Joan and Bill related to each other?

Nug text	Nug relevance	Distiller ID	Nugget text	Degree of membership
They authored the book, <i>Evaluation Made Simple.</i>	1.0	A	They are joint authors.	0.5
		B	They authored the book, <i>Evaluation Made Simple.</i>	1.0
		C	<i>(No nugget provided.)</i>	0.0
		D	<i>(No nugget provided.)</i>	0.0

- The Nug is a fuzzy equivalence class of nuggets
- Meaning of Nug = meaning of its most precise Nugget

Nug 2

- Query: How are Joan and Bill related to each other?

Nug meaning	Nug relevance	Distiller ID	Nugget text	Degree of membership
They wrote the paper, "Further thoughts on evaluation."	1.0	A	They are joint authors.	0.5
		B	They wrote the paper, "Further thoughts on evaluation."	1.0
		C	They wrote the paper, "Further thoughts on evaluation."	1.0
		C	<i>Redundant nugget:</i> They wrote the paper, "Further thoughts on evaluation."	1.0
		D	<i>(No nugget provided.)</i>	0.0

Nug 3

- Query: Where does Joan live? (looking for address)

Nug meaning	Nug relevance	Distiller ID	Nugget text	Degree of membership
Joan lives in Rome, Italy.	0.5 (no address)	A	Joan lives in Italy.	0.5
		B	Joan lives in Rome, Italy.	1.0
		C	Joan lives in Italy's capital.	1.0
		C	<i>Redundant, imprecise nugget:</i> Joan lives in Italy.	0.5
		D	<i>(No nugget provided.)</i>	0.0

Nug analysis for a set of queries

- Count the nugs and count the nuggets from each distiller being evaluated
- Compute statistics for each distiller
 - # *relevant* nugs
 - # *redundant* nuggets (more than one nugget in a nug)
 - # *missed* nugs that were found by other distillers
- Nug analysis determines whether or not different distillers provide nuggets that mean essentially the same thing, no matter how they are expressed

Classical statistical methodology

- For each distiller, use a 2x2 contingency table and two indicator variables (x,y) to define four contingencies involving nugs and nuggets
 - $(x=1, y=1)$ **Relevant nug** and **distiller contributes** a nugget to it
 - $(x=1, y=0)$ **Relevant nug** and **distiller does not contribute** a nugget
 - $(x=0, y=1)$ **Irrelevant nug** and **distiller contributes** a nugget to it
 - $(x=0, y=0)$ **Irrelevant nug** and **distiller does not contribute** a nugget to it

Classical contingency table for a distiller

	$y = 0$	$y = 1$
$x = 0$	# Other	# Wrong
$x = 1$	# Missing	# Right

This classical approach ignores the *relevance weight* of each nug, the *degree of membership* for each nugget, and fails to count *redundant* nuggets as being wrong

Relevance and degree of membership

- To measure *relevance*, *redundancy*, and *degrees of membership*, define three fuzzy descriptors for each distiller
 - R_k = relevance weight of nug k
 - R generalizes the relevance indicator x
 - D_k = largest degree of membership in nug k (for distiller of interest)
 - D generalizes the existence indicator y
 - D_{kj} = degree of membership of the j -th redundant nugget in nug k (redundant nuggets have degrees of membership that do not exceed D_k)
 - All of these fuzzy measures take values on the unit interval $[0, 1]$

Contingency table based on fuzzy counts

- The counts in the contingency table for a specified distiller satisfy these sums over all nuggs

$$\# \text{ Right} = \sum_k R_k D_k$$

$$\# \text{ Wrong} = \sum_k \left((1 - R_k) D_k + \sum_j D_{kj} \right) + \text{Estimated \# Wrong in un-nuggetized text}$$

$$\# \text{ Missing} = \sum_k R_k (1 - D_k)$$

$$\# \text{ Other} = \sum_k (1 - R_k)(1 - D_k) + \text{Estimate of \# Other in the corpora}$$

- Each nugg contributes at most one count to the table
- As $R \rightarrow x$ and $D \rightarrow y$, counting statistics \rightarrow classical values
- Fractional counts are distributed so that relevance and degree-of-membership contributions are statistically independent

Estimating # wrong nuggs in irrelevant text

- Irrelevant text is not nuggetized
- Therefore, the # Wrong (irrelevant) nuggs is estimated from the total number of non-blank characters (# Char) in the distiller's response text

$$\# \text{ Wrong} = \max\left(0, \frac{\# \text{ Char}}{40} - \# \text{ Right}\right)$$

- 40 is the average number of non-blank characters per nug (empirically determined)

Classical performance metrics

	$y = 0$	$y = 1$
$x = 0$	# Other	# Wrong
$x = 1$	# Missing	# Right

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	$y = 0$	$y = 1$
$x = 0$	$P_{xy}(0,0)$	$P_{xy}(0,1)$
$x = 1$	$P_{xy}(1,0)$	$P_{xy}(1,1)$

- Compute the *joint probability distribution* P_{xy} by normalizing the contingency table
- Classical performance metrics are functions of P_{xy}
 - Recall = $P_{y|x}(1,1) = P_{xy}(1,1) / P_x(1)$
 - Precision = $P_{x|y}(1,1) = P_{xy}(1,1) / P_y(1)$
 - F-value = $2 \times \text{Recall} \times \text{Precision} / (\text{Recall} + \text{Precision})$

Proficiency metric

- *Proficiency* measures the fraction of information delivered by the distiller, relative to the total relevant information from all the distillers
- *Proficiency* = normalized mutual information between x and y indicator variables

$$\text{Proficiency} = \frac{I_{XY}}{H_X}$$

$$I_{XY} = \text{mutual information} = \sum_x \sum_y P(x, y) \text{Log}_2 \frac{P(x, y)}{P(x)P(y)}$$

$$H_X = \text{entropy} = -\sum_x P(x) \text{Log}_2 P(x)$$

Interpretation of Proficiency

- Takes values on the unit interval $[0, 1]$
- Value 0 means that the distiller provides no relevant information
- Value 0.75 means that the distiller provides 75% of the relevant information delivered by all the distillers being considered

Bayesian analysis

- For small samples, we recommend a Bayesian correction to the contingency table (CT)
- For example, add 1/4 pseudo count to each cell of the CT
 - This avoids zero counts and zero probabilities caused by small sample sizes
 - The performance metrics are then always well defined and take reasonable values, even with small amounts of evidence
 - With no data, the prior values for recall and precision are each $\frac{1}{2}$, and the proficiency is 0

Example performance metrics (1/2)

- We use contingency tables based on Nugs 1 – 3
- We assume the corpora contain on order of 10^5 nugs
- # Wrong in *irrelevant text* (not shown) is estimated from character counts

Estimated # Wrong

Distiller	# Wrong
A	1.50
B	1.00
C	0.75
D	0.00

Example performance metrics (2/2)

Based on raw empirical probabilities

Distiller	Precision	Recall	Proficiency
A	0.417	0.500	0.400
B	0.625	1.000	0.909
C	0.154	0.333	0.234
D	(undefined)	0.000	0.000

These extreme values reflect the small sample size

Based on Bayesian probabilities

Distiller	Precision	Recall	Proficiency
A	0.429	0.500	0.400
B	0.611	0.917	0.811
C	0.200	0.375	0.271
D	0.500	0.083	0.066

The *Proficiency* provides rank ordering of distillers based on relative information content

Conclusion

- Information distillers generate English response text from both structured and unstructured multilingual sources
- We have developed a statistical methodology for evaluating such distillers, which measures
 - Relevance
 - Redundancy
 - Recall
 - Precision
 - Proficiency (quantity of information provided)