

Automated Summarization System

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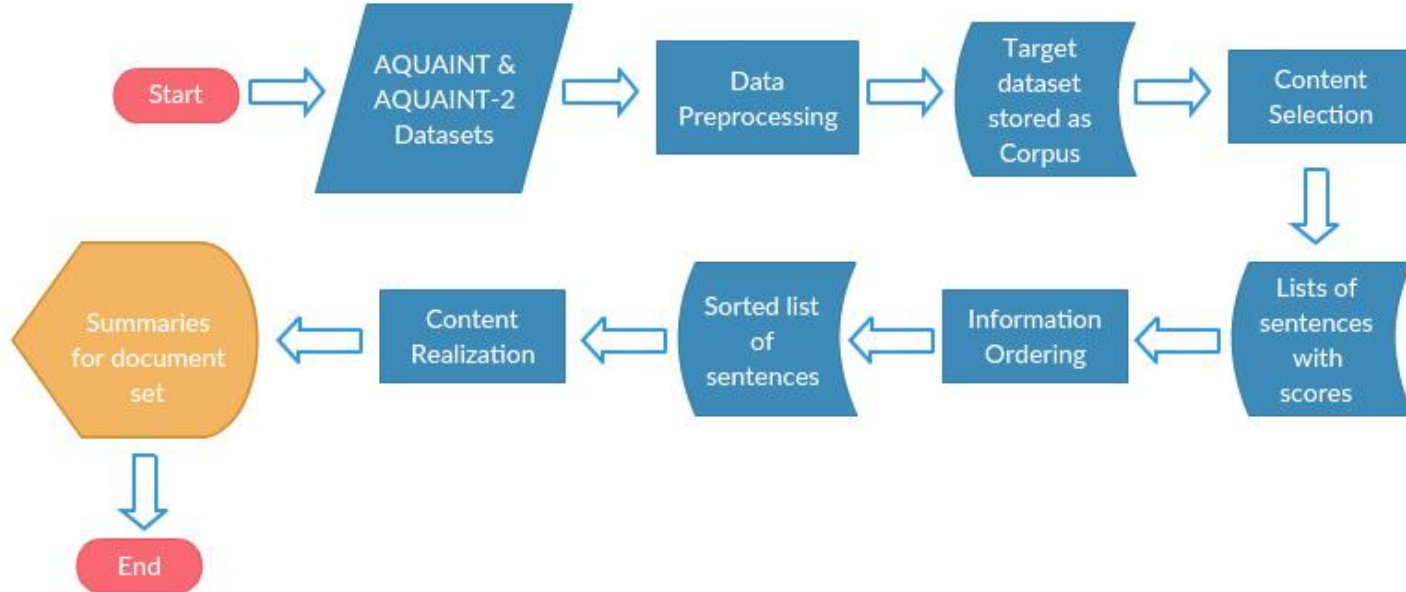
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Overview: Improved System

- Combination of both unsupervised and supervised methods
- Extraction-based approach without modifying sentences
- Three parts:
 - Improvement of Content Selection
 - Information Ordering
 - Content Realization

System Flowchart





Improvement of Content Selection

Two Salient Score:

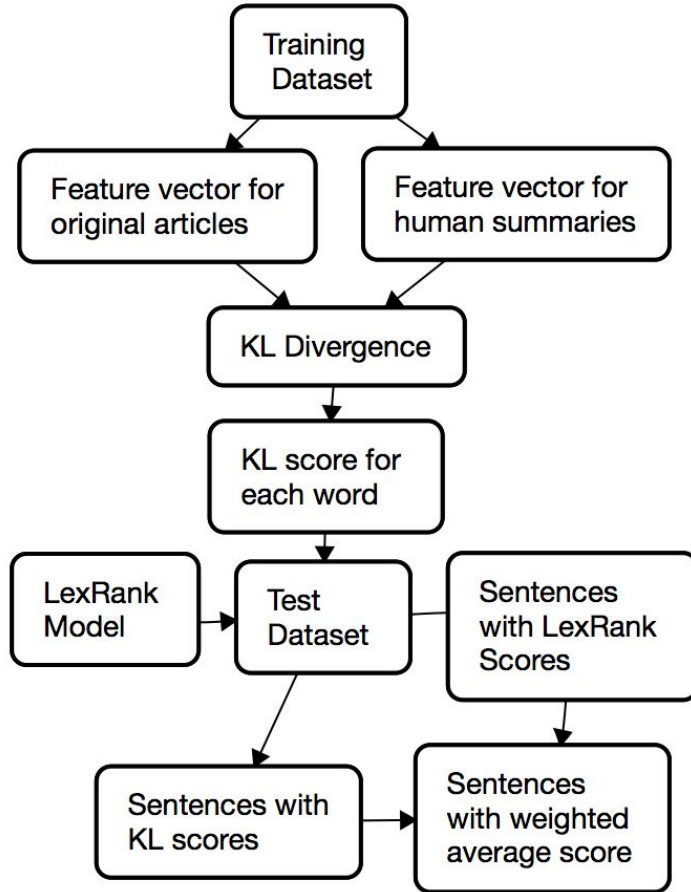
1. Salient score based on LexRank algorithm
2. Salient score based on Kullback–Leibler (KL) divergence

Final Salient Score:

Weighted average of the two salient score

Other Constraints:

Sentence length must be longer than 8



Content Selection Flow chart



Calculate Word KL-Score

- Build model on articles (A) and human summaries (S)
- Two KL-scores for a word (w)

$$\text{KL}(S || A)(w) = Pr_S(w) \times \ln \left(\frac{Pr_S(w)}{Pr_A(w)} \right) \quad \text{KL}(A || S)(w) = Pr_A(w) \times \ln \left(\frac{Pr_A(w)}{Pr_S(w)} \right)$$

- Final KL-Score of a word (w)

$$Score_{KL}(w) = \frac{1}{2} (\text{KL}(S || A)(w) - \text{KL}(A || S)(w))_+$$



Calculate Sentence Salient Score

- KL salient Score of a sentence

$$Score_{KL}(sent) = \frac{\sum_{w \in sent} Score_{KL}(w)}{length(sent)}$$

- LexRank salient Score of a sentence

$$Score_{LR}(sent) = LexRank(sent, docset)$$

- Normalize the two score
- Weighted average salient score

$$Score(sent) = 0.25 \times Score_{LR}(sent) + 0.75 \times Score_{KL}(sent)$$



Information Ordering

- Chronological Expert (Bollegala et al.)
 - Define a preference function as:
 - $T(u)$ is the publication time of sentence u .
 - $D(u)$ is the unique id code of sentence u 's document.
 - $N(u)$ is the in-text index of sentence u in its document.

$$\text{PREF}_{\text{chro}}(u, v, Q) = \begin{cases} 1 & T(u) < T(v) \\ 1 & [D(u) = D(v)] \wedge [N(u) < N(v)] \\ 0.5 & [T(u) = T(v)] \wedge [D(u) \neq D(v)] \\ 0 & \text{otherwise} \end{cases}.$$



Information Ordering

- Chronological Expert (Bollegala et al.)
 - Sentence Ordering Algorithm

Algorithm 1 Sentence Ordering Algorithm.

Input: A set \mathcal{X} of the extracted (unordered) sentences and a total preference function $\text{PREF}_{total}(u, v, Q)$.

Output: Ranking score $\hat{\rho}(t)$ of each sentence $t \in \mathcal{X}$.

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1:  $\mathcal{V} = \mathcal{X}$ 
2:  $Q = \emptyset$ 
3: for each  $v \in \mathcal{V}$  do
4:    $\pi(v) = \sum_{u \in \mathcal{V}} \text{PREF}_{total}(v, u, Q) - \sum_{u \in \mathcal{V}} \text{PREF}_{total}(u, v, Q)$ 
5: end for
6: while  $\mathcal{V} \neq \emptyset$  do
7:    $t = \arg \max_{u \in \mathcal{V}} \pi(u)$ 
8:    $\hat{\rho}(t) = |\mathcal{V}|$ 
9:    $\mathcal{V} = \mathcal{V} - \{t\}$ 
10:   $Q = Q + \{t\}$ 
11:  for each  $v \in \mathcal{V}$  do
12:     $\pi(v) = \pi(v) + \text{PREF}_{total}(t, v, Q) - \text{PREF}_{total}(v, t, Q)$ 
13:  end for
14: end while
15: return  $\hat{\rho}$ 
```



Information Ordering

Input: a list of selected sentences.

Do:

- Compute chronological preference of each sentence pair.
- Order sentences using Algorithm 1

Output: a list of sentences with ranking scores.



Content Realization

We improved our **Integer Linear Programming** content realization approach:

- Instead of considering salience score of the sentence, we use the weight sum of bigrams as the new target function
 - By maximizing target function, the redundancy is minimized implicitly
 - For a bigram, we count the number of sentences which contain this bigram as its weight
- Three constraints: one for length limitation and two for establishing the relation between bigram variables and sentence variables
- Rewrite the whole module -- migrate from scipy's linprog to PuLP



Prune sentences

We tried 3 approaches to compress the sentence:

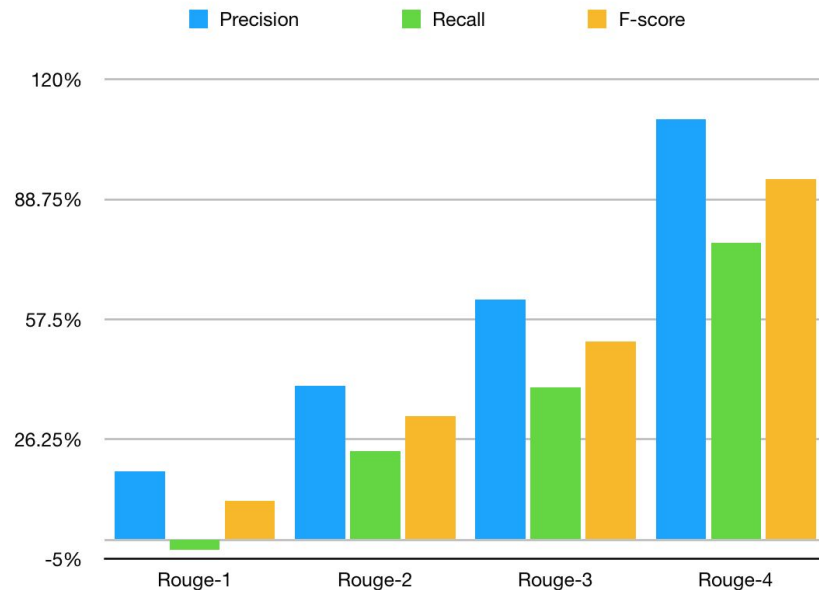
- Remove clauses starting with an adverb
- Remove appositions
- Remove contents in a pair of parenthesis

Unfortunately, all three approaches have negative effect, based on ROUGE score. So we didn't activate any sentence compression methods in our submission

Results and Analysis

Table 1: ROUGE Results for devtest

ROUGE	Recall	Precision	F-score
ROUGE-1	0.23619	0.24349	0.24384
ROUGE-2	0.06092	0.06541	0.06292
ROUGE-3	0.01981	0.02088	0.02028
ROUGE-4	0.00746	0.00768	0.00755





Issues and Successes

Issues:

- Randomness in small subset of document sets
- Minor fluctuation in Rouge scores
- Extraction-based method, does not modify sentence content or combine several sentences into one.
- The balance between supervised and unsupervised methods

Successes:

- Big improvement over the baseline system, some aspects achieve a 100%+ improvement.
- Combination of both unsupervised and supervised learning methods



Strategies for Group Work

- Weekly meeting on Sunday night, discuss this week's work and coordinate next week's tasks.
- Two members worked on Content Selection, two worked on Information Ordering.
- At the same, each member make some minor improvements for its own part during the baseline system development.
- Mainly used github for code sharing and coordination.



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