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A Statistical NLG Framework for Aggregated Planning and Realization

Ravi Kondadadi, Blake Howald and Frank Schilder Research & Development, Thomson Reuters

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OVERVIEW

- Background on approaches to NLG
- A statistical framework to NLG
 - Clustering templates
 - Learning sentence and document planning
- Developed systems applied to *Biography* and *Weather* domains
- Evaluations:
 - Automatic Metrics (BLEU-4, METEOR, Syntactic Variability)
 - Non-Expert crowdsourcing (CrowdFlower)
 - Expert evaluations (Biography)
- Conclusions



NLG SYSTEM ARCHITECTURE (Reiter & Dale 2000)

- Data/Communicative Goal
 - Provide textual information about some subject matter/ domain
- Document (Macro-) Planning
 - "What to say" (Content)
 - Content selection
 - Document structuring
- Sentence (Micro-) Planning
 - "How to say" (Sentence)
 - Word choice, phrase composition, pronoun use and resolution, etc.
- Surface realization

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 Putting everything together into "natural" sounding texts

Input Data & **Communicative Goal** Document Planner Document plan Sentence Planner Text specification Surface realizer Text

BACKGROUND

• Our system is a hybrid statistical-template system

- Templates avoid necessity of an extensive grammar
- Statistical approach, provided a robust corpus, allows for expedited learning of :
 - <u>Content Selection</u> organization of the semantic structure of historical data
 - <u>Document Planning</u> sequence of templates and domain tags
 - <u>Sentence Planning</u> domain general and specific tagging and template generation

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<u>Surface Realization</u> – template selection and content filling



NLG FRAMEWORK



CREATING TEMPLATE BANKS

- Automatic clustering (k-Means) and manual review creates template banks
- Template banks contains clusters of templates derived from corpus via NE tagging and semantic analysis:
 - a. ...
 - *b.* [*person]* holds a [degree] in [subject] from [school] and a [degree] from [school]
 - *c.* [*person*] graduated from [school] with a degree in [subject]
 - d. [person] graduated from [school] with a degree in [subject] and also a [degree] in [subject]
 - e. [person] received a [degree] from [school] in [date]
 f. ...
- Conceptual Units are manually assigned to clusters:
 - Culd: 001 "current position";
 - Culd: 002 "previous position";
 - Culd: 003 "education";



COLLECTION OF CORPUS STATISTICS

- Frequency distribution of templates overall and per position
- Frequency distribution of Culds overall and per position
- Average number of words per Culd, position and combination of both
- Average number and distribution of entity tags by Culd
- Average number and distribution of entity tags by position
- Frequency distribution of Culd sequences (bigrams and trigrams)
- Frequency distribution of template sequences (bigrams and trigrams)
- Frequency distribution of entity tag sequences overall and per position
- The average, minimum, maximum number of Culds across all documents



FEATURES FOR RANKING SVM

- Feature values are binary (1|0) or real values [0..1]
 - Culd given position
 - Overlap of named entities
 - Prior template/ Culd
 - Difference in number of words given position
 - Percentage of unused data/ Average number of words used
 - Difference in number of named entities
 - Average number of entities
 - Most likely Culd given position and previous Culd
 - Similarity between the most likely template in Culd and current template



RANKING

- Training (70%) for each template in all training documents:
 - 1. All other templates in Culd (filtered by entities) are ranked by Levenshtein edit distance
 - 2. Corpus statistics used to calculate all features for each ranked template
 - 3. Ranking SVM assigns model weights to all features
- Testing / Generation (30%)
 - 1. Select most likely Culd for position 1 given input data
 - 2. Filter templates by input data
 - 3. Score all remaining templates (multiplying feature values by model weights)
 - 4. Select top scored template, fill input data
 - 5. Remove or modify used input data
 - 6. Repeat until input data exhausted (within average min/max length)



DATA

- Biography Human generated (journalists)
 - Corporate officers and directors biographies
- *Weather* Human generated (weather forecasters)
 - Offshore oil rig weather forecasts (SumTime-Meteo (Reiter et al. 2005))

	Biography	Weather
Texts (Sentence Range)	1150 (3-17)	1045 (1-6)
Conceptual Units	19	9
Templates	2836	2749
Template per Conceptual Unit (Range)	236 (7-666)	305 (6-800)



EVALUATIONS

- Original texts compared against Rank and Non-Rank with automatic metrics (Biography = 350; Weather = 209):
 - <u>BLEU-4</u> 4-gram overlap
 - <u>METEOR</u> unigram weighted f-score less penalty based on chunking dissimilarity
 - <u>Syntactic Variability</u> percentage of unique template sequences across all documents
 - Higher value (closer to 1) indicates that documents in a collection are linguistically different
 - Lower value (closer to 0) indicates that documents in a collection are linguistically similarly



Automatic Evaluations – *Syntactic Variability*



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Automatic Evaluations – BLEU-4 & METEOR





AUTOMATIC METRICS

- Variability: Rank has about the same variability as the original text.
- BLEU-4: Rank is lower than NonRank
- METEOR: Rank is higher than NonRank
- Automatic metrics BLEU-4 and METEOR are not very sensitive to Content selection and Document planning:



NON-EXPERT CROWDSOURCE EVALUATION

- Two tasks on Crowdflower:
 - Sentence Preference
 - Text Understandability
- Native English speakers with geographic restriction (US, UK, Australia, etc.)
- Four initial gold data responses required
 - no more than 50 responses total per person (IP address)
 - one additional gold question every four questions had to be answered correctly to continue
- Radio buttons separated from text to avoid click bias



SENTENCE PREFERENCES

- You will be shown a pair of sentences expressing the same idea, for example "the cat is sitting on the mat" vs. "the cat is on the mat".
 - For each pair of sentences, indicate, as quickly as possible, which sentence you prefer.
 - Preference should be based on understandability (ease of reading, grammaticality) and informativeness (is one more informative than the other?).
- 80 sentences from *Biography*, 74 from *Weather*
- 8 judgments per sentence pair
- 3758 total judgments
- 75.87% average agreement



SENTENCE-PREFERENCE - Weather





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SENTENCE-PREFERENCE - *Biography*





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TEXT UNDERSTANDABILITY

- Please rate the understandability of the following texts:
 - 1 = Disfluent Main point is not clearly understood. Severe issues with informativeness and grammar.
 - 3 = Understandable Main point is understood. Few issues with informativeness and grammar.
 - 5 = Fluent Created by a native speaker and experienced writer. Appropriately informative with no grammatical mistakes.
- 120 texts per domain (240 total)
- 8 judgments per text
- 1920 total judgments
- 69.51% average agreement



TEXT UNDERSTANDABILITY– FLUENT ("5") RATINGS





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EXPERT BIOGRAPHY EVALUATION

- Sentence-Preference
 - 3 judgments per sentence (76.22% agreement)
 - Similar trend as the non-expert crowd
 - Original preferred over Rank and NonRank
 - But, *NonRank* preferred 70% to the *Rank*'s (30%)
- Text-Understandability
 - 3 judgments per document (72.95% agreement)
 - Similar trend as the non-expert crowd
 - Original had a higher fluency than the Rank and NonRank
 - But, NonRank had 10% higher "Fluent" rating (58.22%) compared to the Rank (47.97%)
- Why? NonRank generations are shorter and more concise – in keeping with editorial standards,
 - Note that training data didn't always follow this guideline.



CONCLUSIONS AND DISCUSSION

- Conclusions
 - NLG generation technique:
 - New NLG framework combining learning templates and selecting content/document structure via a Ranking SVM
 - Framework is domain adaptable
 - Evaluation:
 - New automatic evaluation metric for syntactic variability
 - Crowd-source evaluation
 - showed advantage of Ranking approach for overall fluency for biography data
 - Indicated problems with domain-specific language for the weather reports
 - Expert evaluation
 - provided feedback on preferred style for biography data
- Next Steps
 - Address data consumption and its relation to coreference generation
 - Automatic template generation



Thank You!

Questions?

frank.schilder@thomsonreuters.com

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