Evaluation of Text Generation: Automatic Evaluation vs. Variation

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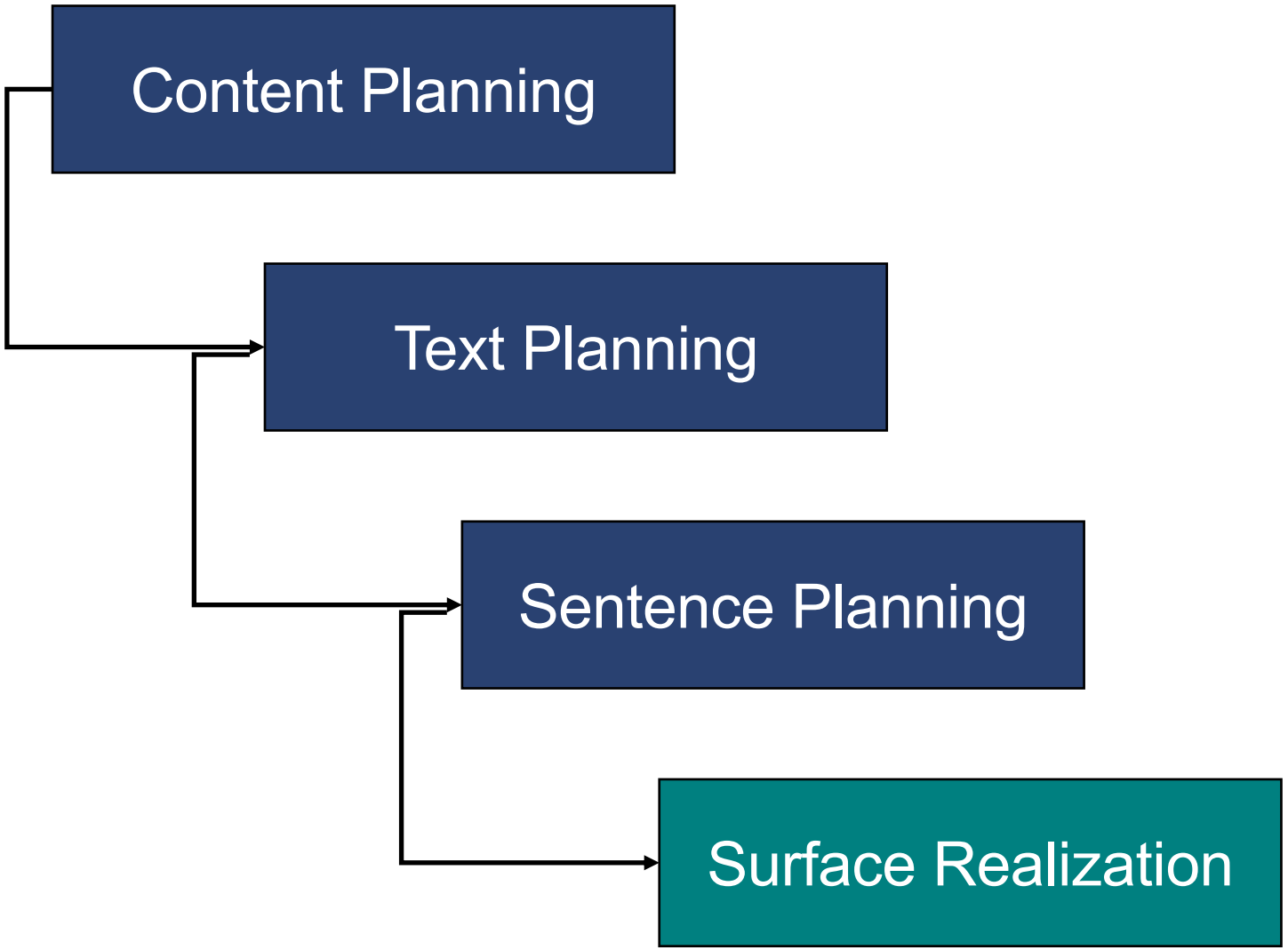
Natural Language Generation



Approaches to Surface Realization

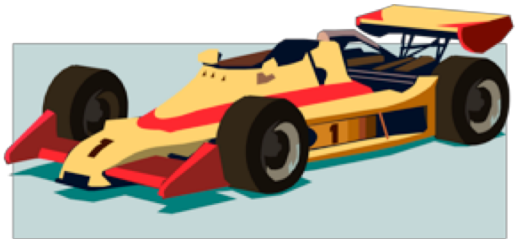
- Template based
  - Domain-specific
  - All output tends to be high quality because highly constrained
- Grammar based
  - Typically one high quality output per input
- Forest based
  - Many outputs per input
- Text-to-text
  - No need for other generation components

Surface Realization Tasks

- To communicate the input meaning as *completely, clearly* and *elegantly* as possible by careful:
  - Word selection
  - Word and phrase arrangement
  - Consideration of context

Importance of Lexical Choice

I drove to Rochester.



I raced to Rochester.

I went to Rochester.

Importance of Syntactic Structure

- *I picked up my coat three weeks later from the dry cleaners in Smithtown*
- *In Smithtown I picked up my coat from the dry cleaners three weeks later*

Evaluating Text Generators

- Per-generator: Coverage
- Per-sentence:
  - Adequacy
  - Fluency / syntactic accuracy
  - Informativeness
- Additional metrics of interest:
  - Range: Ability to produce valid variants
  - Readability
  - Task-specific metrics
    - E.g. for dialog

Evaluating Text Generators

- Human judgments
- Parsing+interpretation
- Automatic evaluation metrics – for generation or machine translation
  - Simple string accuracy+
  - NIST*
  - BLEU*+
  - F-measure*
  - LSA

+ Question

What is a “good” sentence?

fluent

adequate

readable

Approach

- Question: Which evaluation metric or set of evaluation metrics least punishes variation?
  - Word choice variation
  - Syntactic structure variation
- Procedure: Correlation between human and automatic judgments of variations
  - Context not included

Lexical and Syntactic variation

*(a) I bought **tickets** for the show on **Tuesday**.*

*(b) It was the show on **Tuesday** for which I bought **tickets**.*

*(c) I **got** **tickets** for the show on **Tuesday**.*

*(d) I bought **tickets** for the **Tuesday** show.*

*(e) On **Tuesday** I bought **tickets** for the show.*

*(f) For the show on **Tuesday** **tickets** I bought.*

String Accuracy

- Simple String Accuracy
  - (I+D+S) / #Words (Callaway 2003, Langkilde 2002, Rambow et. al. 2002, Leusch et. al. 2003)
- Generation String Accuracy
  - (M + I' + D' + S) / #Words (Rambow et. al. 2002)

The	dog	saw			the	man
The	man	was	seen	by	the	dog
	M	S	D	D		M
	I, D					I, D

BLEU

- Developed by Papenini et. al. at IBM
- Key idea: count matching subsequences between the reference and candidate sentences
- Avoid counting matches multiple times by clipping
- Punish differences in sentence length

The	dog	saw	the	man		
The	man	was	seen	by	the	dog

NIST ngram

- Designed to fix two problems with BLEU:
  - Geometric mean penalizes large N
  - Might like to prefer ngrams that are more informative = less likely
- Arithmetic average over all ngram co-occurrences
- Weight “less likely” ngrams more
- Use a brevity factor to punish varying sentence lengths

F Measure

- Idea due to Melamed 1995, Turian et. al. 2003
- Same basic idea as ngram measures
- Designed to eliminate “double counting” done by ngram measures
- F = 2*precision*recall / (precision + recall)
- Precision(candidate|reference) = maximum matching size(candidate, reference) / |candidate|
- Precision(candidate|reference) = maximum matching size(candidate, reference) / |reference|

F Measure

the	?					?	
dog						?	
saw							
the	?					?	
man	?						
	the	man	was	seen	by	the	dog

+ LSA

- Doesn’t care about word order
- Evaluates how similar two bags of words are with respect to a corpus
  - Measures “similarity” with coccurrence vectors
- A good way of evaluating word choice?

Eval. Metric	Means of measuring fluency	Means of measuring adequacy	Means of measuring readability	Punishes length differences?
SSA	Comparison against reference sentence	Comparison against reference sentence	Comparison against reference sentence from same context*	Yes (punishes deletions, insertions)
NIST n-gram, BLEU	Comparison against reference sentences -- matching n-grams	Comparison against reference sentences	Comparison against reference sentences from same context*	Yes (weights)
F measure	Comparison against reference sentences -- longest matching substrings	Comparison against reference sentences	Comparison against reference sentences from same context*	Yes (length factor)
LSA	None	Comparison against word co-occurrence frequencies learned from corpus	None	Not explicitly

+ Experiment 1

- Sentence data from Barzilay and Lee's paraphrase generation system (Barzilay and Lee 2002)
  - Includes word choice variation, e.g.
    - *Another person was also seriously wounded in the attack* vs
    - *Another individual was also seriously wounded in the attack*
  - Includes word order variation, e.g.
    - *A suicide bomber blew himself up at a bus stop east of Tel Aviv on Thursday, killing himself and wounding five bystanders, one of them seriously, police and paramedics said*
    - *A suicide bomber killed himself and wounded five, when he blew himself up at a bus stop east of Tel Aviv on Thursday*

Paraphrase Generation

1. Cluster like sentences
   - By hand or using word n-gram co-occurrence statistics
   - May first remove certain details
2. Compute multiple-sequence alignment
   - Choice points and regularities in input sentence pairs/sets in a corpus
3. Match lattices
   - Match between corpora
4. Generate
   - Lattice alignment

Paraphrase Generation Issues

- Sometimes words chosen for substitution carry unwanted connotations
- Sometimes extra words are chosen for inclusion (or words removed) that change the meaning

Discussion

- These metrics achieve some level of correlation with human judgments of adequacy
  - But could we do better?
- Most metrics are negatively correlated with fluency
  - Word order or constituent order variation requires a different metric
- Automatic evaluation metrics other than LSA punish word choice variation
- Automatic evaluation metrics other than LSA punish word order variation
  - Are not as effected by word order variation as by word choice variation
  - Punish legitimate and illegitimate word and constituent reorderings equally

Discussion

- Fluency
  - These metrics are not adequate for evaluating fluency in the presence of variation
- Adequacy
  - These metrics are barely adequate for evaluating adequacy in the presence of variation
- Readability
  - These metrics do not claim to evaluate readability

A Preliminary Proposal

- Modify automatic evaluation metrics as follows:
  - Not punish legitimate word choice variation
    - E.g. using WordNet
    - But the ‘simple’ approach doesn’t work
  - Not punish legitimate word order variation
    - But need a notion of constituency

Another Preliminary Proposal

- When using metrics that depend on a reference sentence, use
  - A set of reference sentences
    - Try to get as many of the word choice and word order variations as possible in the reference sentences
  - Reference sentences from the same context as the candidate sentence
    - To approach an evaluation of readability
  - And combine with some other metric for fluency
    - For example, a grammar checker

A Proposal

- To evaluate a generator:
  - Evaluate for coverage using recall or related metric
  - Evaluate for ‘precision’ using separate metrics for fluency, adequacy and readability
    - At this point in time, only fluency may be evaluable automatically, using a grammar checker
    - Adequacy can be approached using LSA or related metric
    - Readability can only be evaluated using human judgments at this time

Current and Future Work

- Other potential evaluation metrics:
  - *F measure plus WordNet*
  - *Parsing as measure of fluency*
  - F measure plus LSA
  - Use multiple-sequence alignment as an evaluation metric
- Metrics that evaluate readability