

Two-Stage Stochastic Natural Language Generation for Email Synthesis by Modeling Sender Style and Topic Structure

Yun-Nung (Vivian) Chen and Alexander I. Rudnicky



sender-specific

mixture

model P_i^s

1. The Task

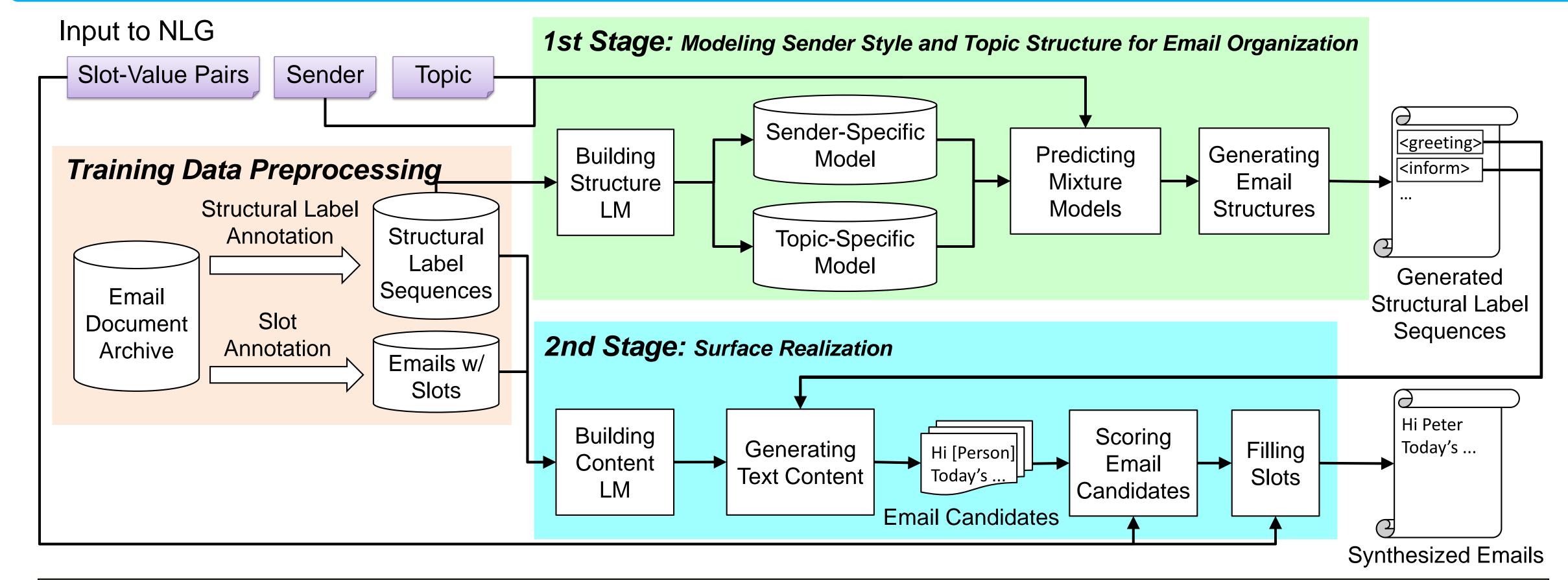
Motivation

- Generate emails that reflect sender style and intent of communication
- Provide emails as part of synthetic evidence of insider threats for purposes of training, prototyping, and evaluating anomaly detectors.

> Approach

- Senders' characteristics are modeled based on their writing patterns (structure, politeness, etc.) instead of their attitudes
- 1st Stage: modeling sender style and topic structure for email organization
- 2nd Stage: stochastic generation of language for surface realization

2. The Framework

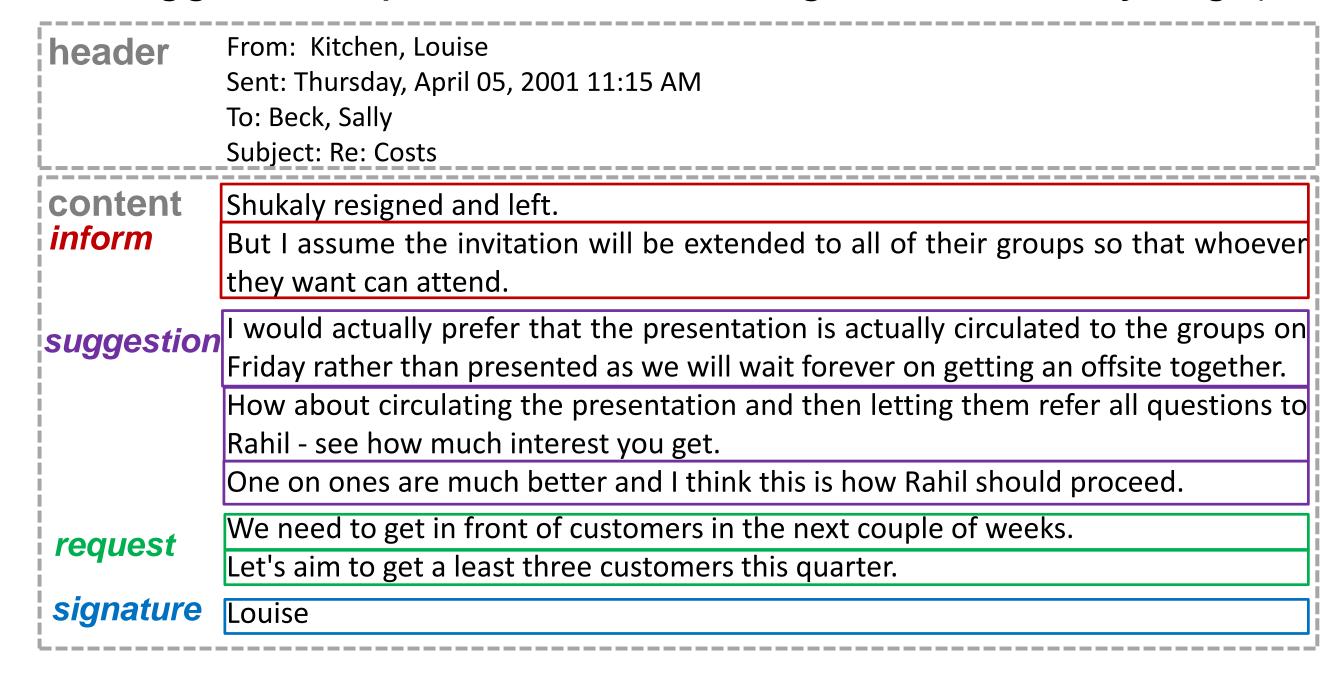


- > 1st stage structures the emails according to sender style and topic structure (high-level generation)
- > 2nd stage synthesizes text content based on the particulars of an email element and the goals of a given communication (surface-level realization).

3. Training Data Preprocessing

Structural Label Annotation

o 10 email structure elements (*greeting, inform, request, suggestion, question, answer, regard, ack., sorry, sign*)



Different senders tend to structure emails in different ways.

Slot Annotation

- General class: 7-class extracted by Named Entity Recognition (*location, person, org., time, money, percent, date*)
- Topic class: 3-class extracted by keywords (*meeting*, issue, discussion)

4. Modeling Sender Style and Topic Structure for Email Organization

• Each email can be treated as a structural label sequence

For each structural label:

- 1) Building Structure Language Models
 - Sender-specific structure LM (trigram w/ smoothing)
 - Topic-specific structure LM (trigram w/ smoothing)

 - A sender may have personal style about email structure.
 Emails about the same topic may have similar structures.
- 2) Predicting Mixture Models

$$P_{i,j}(l) = \alpha P_i^s(l) + (1 - \alpha) P_i^t(l)$$



Generate structural label sequences randomly according to dist. of mixture models

5. Surface Realization

For each structural label:

- Build Content Language Model
 - Cross-sender content LMs
 (5-gram w/o smoothing)

For each generated structural label:

- 1) Stochastically Generate Text Content
- 2) Score Email Candidates
 - We penalize the synthesized email if it:
 - contains slots without provided values
 - doesn't have the required slots

3) Fill Slots

- Tomorrow's [meeting] is at [location].
- → Tomorrow's speech seminar is at Gates building.

topic-specific

model $P_{\dot{i}}^t$

(%)	Template	Stochastic	No Diff
Coherence	36.19	38.57	25.24
Fluency	28.10	40.48	31.43
Naturalness	35.71	45.71	18.57
Preference	36.67	42.86	20.48
Overall	34.17	41.90	23.93

The ratio of subjects' preference according to different criteria

6. Experiments

Evaluation of Sender Style Modeling

- Rate synthesized emails for each sender on a scale of 1 (highly confident that email is not from the sender) to 5 (highly confident that email is from the sender)
- Average normalized scores the corresponding senders receive: 45% > 33% [for 3 senders]
- > Sender style can be noticed by subjects based on greeting usage, politeness, the length of email, etc.

Evaluation of Surface Realization

- Compare template-based generation (sentence-level NLG) and stochastic generation (word-level NLG) on the same email structures.
- > The word-based stochastic generation outperforms the template-based algorithm and requires less effort in terms of knowledge engineering.

7. Conclusions

- We propose a two-stage stochastic NLG process for email synthesis that models sender style and topic structure.
- Subjects can detect sender style and can differentiate template-based (sentence-level) and stochastically-generated sentences (word-level).
- This technique can be used to create realistic emails and that email generation could be carried out using mixtures containing additional models based on other characteristics.
- The current study shows that email can be synthesized using a small corpus of labeled data; however these models could be used to bootstrap the labeling of a larger corpus which in turn could be used to create more robust models.