COM6115: Text Processing

Natural Language Generation 3

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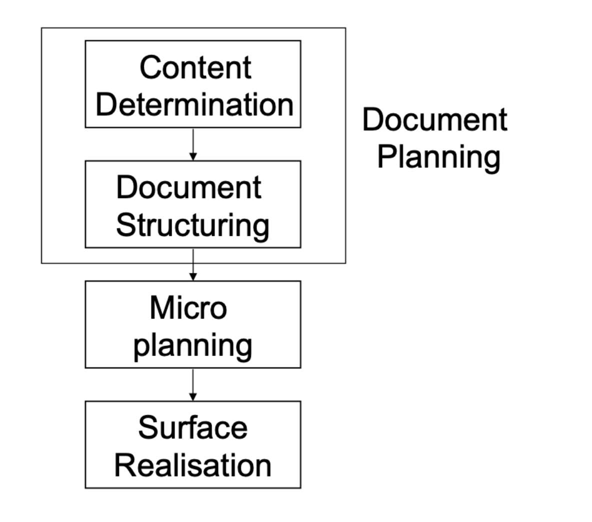
The Architectural View



Microplanning

- Second stage of NLG
  - Choosing language to express content
- Several subtasks
  - Lexical choice: Which words to use
  - Reference: How to refer to objects
  - Aggregation: How/when combine phrases into sentences

Microplanning

- Problem: There are zillions of ways of expressing a message in words
  - John sold the book to Mary
  - Mary bought the book from John
  - John sold the book. Mary bought it
  - Etc, etc
- Which one should we use?

Approaches

- Theoretical
  - Define what "best" means, make microplanning choices that optimise it
  - Hard to do in practice because we don't have good models of the effects of choices
- Pragmatic
  - Imitate corpus
    - Use statistical learning if corpus large enough
  - Problem: sometimes corpus texts may not be very good from a microplanning perspective

Lexical choice

- Lexical choice: the task of choosing the right words or lemmas to express the contents of the message
- I.e., which word should be used to communicate a concept?
  - Buy vs sell
  - Ascended vs rose vs surfaced
  - Too fast vs too rapidly
  - Recommend vs suggest
  - etc

Issues that affect lexical choice

- Frequency (affects readability)
  - lie vs prevarication
- Formality:
  - Error vs howler
- Focus, expectations
  - not many, few, a few, only a few [students failed the exam]
- Technical terms
  - (statistics) standard <u>error</u>, not
  - standard <u>mistake</u>
- Convention
  - Temperature <u>falls</u>, Wind speed <u>eases</u>

Corpus-based Approach: Example

Statistics-Based Lexical Choice for NLG from Quantitative Information

Motivation

- NLG systems express information in human language

Forecasted numeric data		
Wind Direction (azimuth)	Wind Speed (knots)	Gust (knots)
2	9	11
92	20	30
130	4	5

Forecast Text
SE 10-12
E 20-22 GUSTS 30
MAINLY 8 OR LESS

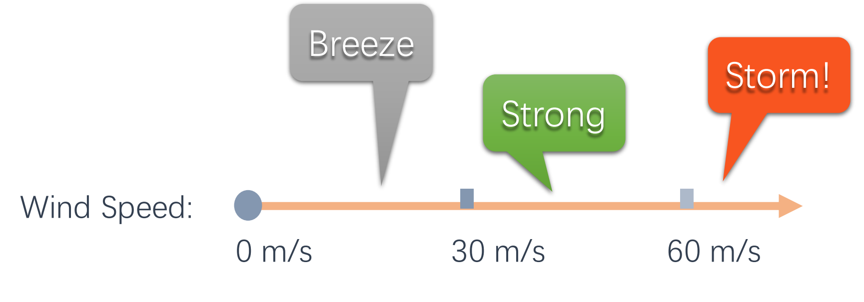
Motivation

- Systems need to "know" what expressions are most suitable for expressing a given piece of information.

wd=130	→	**"SE"**
wd=92	→	**"E"**
ws=4	→	**"8 OR LESS"**

Motivation

- Systems need to "know" what expressions are most suitable for expressing a given piece of information.



Our Goal

- To develop a statistical algorithm for lexical choice for quantitative information, which can
  - ◇ Detect the relationship between data dimensions (aka. attributes) and words
  - ◇ Does not rely on hand-crafted rules;
  - ◇ Predict both when and which word(s) should be used;
  - ◇ One word can refer to multiple dimensions.

P("muggy" | ws=20,temp=35,humid=97,...)

Methodology

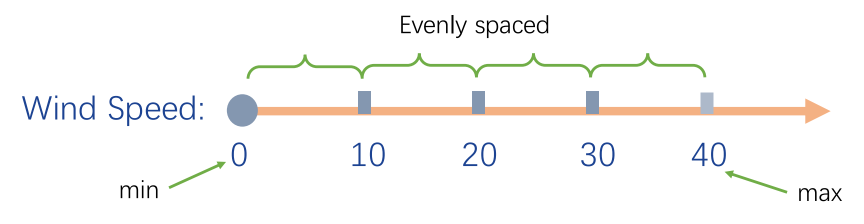
- Each data record consists of attribute-value pairs.
- E.g., dir=2,ws=9,gusts=11, where the attributes are "dir", "ws", and "gusts".

Forecasted	**numerical**	**data**
Wind Direction (azimuth)	**Wind Speed (knots)**	**Gust (knots)**
2	**9**	**11**
92	**20**	**30**
130	**4**	**5**

Representing Data in Vector

We represent each attribute (e.g. wind speed) as a combination of some weighted key-points.

- The key-points are derived by:
  - ◇ Taking the min and max values of the attribute (from training data)
  - ◇ Key-points are evenly spaced between the min and max values
- The number of the key-points for an attribute are fixed



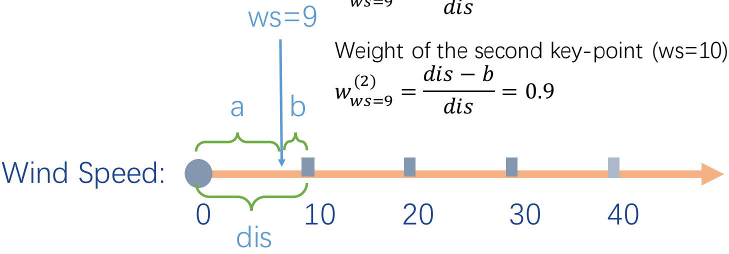
An example of deriving the key point weights for the attribute value ws=9 (i.e., wind speed dimension).

Weight of the first key-point (ws=0) for ws=9:

$$w_{ws=9}^{(1)} = \frac{dis - a}{dis} = 0.1$$

Weight of the second key-point (ws=10) for ws=9:

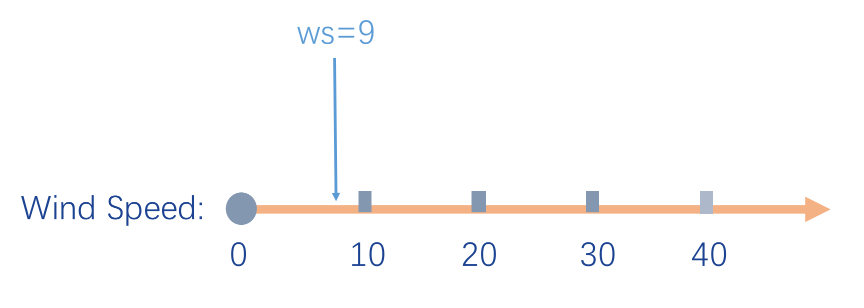
$$w_{ws=9}^{(2)} = \frac{dis - b}{dis} = 0.9$$



Data Representation

An example of deriving the key point weights for the data record ws=9 (i.e., wind speed dimension).

- In this way, an attribute value (e.g. ws=9) can be represented by a key point weight vector
- I.e. the weight vector of ws=9 is [0.1, 0.9, 0, 0, 0].



Representing Data in Vector

Similarly, a data record (i.e., a set of attribute-value pairs) can be represented by multiple groups of key-points, e.g.:

$ws = 9 \rightarrow [0.1, 0.9, 0, 0, 0]$
$dir = 2 \rightarrow [0.97, 0.03, 0, 0, 0]$

Thus, to represent a set of attribute-value pairs, we concatenate the individual weight vectors, e.g.:

$\{ws = 9, dir = 2\} \rightarrow [0.1, 0.9, 0, 0, 0, 0.97, 0.03, 0, 0, 0]$

Representing Data in Vector

The entire data-text corpus can then be represented with a vector matrix (**K**), whose row corresponds to the weight vector of a data record.

$$\begin{array}{c} \{ws = 9, dir = 2, \dots\} \\ \{ws = 20, dir = 130, \dots\} \\ \{ws = 2, dir = 90, \dots\} \\ \dots \end{array} \rightarrow \boldsymbol{K} = \begin{array}{c} \begin{array}{cc} \overbrace{\qquad\qquad\qquad\qquad}^{\text{Wind speed}} & \overbrace{\qquad\qquad\qquad\qquad}^{\text{Wind direction}} \end{array} \\ \begin{bmatrix} 0.1 & 0.9 & 0 & 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 & \dots \\ 0 & 0 & 1 & 0 & 0 & 0 & 0.66 & 0.44 & 0 & 0 & \dots \\ 0.8 & 0.2 & 0 & 0 & 0 & 1 & 0.86 & 0.14 & 0 & 0 & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} \end{array}$$

Representing Text

- We use a column vector (namely $\mathbf{e}_i$)to represent the text of a data record Each element of $\mathbf{e}_i$ indicates whether a word appears in the data record, e.g.:

Forecast Text
SE 10-12
E 20-22 GUSTS 30
MAINLY 8 OR LESS
...

SE, E, MAINLY, GUSTS, 10, 12, 20, 22, 30, 8, OR, LESS, -

[1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1]
[0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1]
[0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0]
...

$\mathbf{e}_{MAINLY}$ $\mathbf{e}_{22}$

Representing Words in Vector

- So far, data are represented by weight vectors, whose values can be calculated using key points.
- We represent words in the corpus using the same weight vectors whose values are unknown.

$$\{ws = 9, dir = 2\} \rightarrow v_{data} = [0.1, 0.9, 0, 0, 0, 0.97, 0.03, 0, 0, 0]$$
$$\text{"}muggy\text{"} \rightarrow v_{muggy} = [?, ?, ?, ?, ?, ?, ?, ?, ?, ?]$$

Methodology

Task: To estimate v_i for word i given a data-to-text corpus as input.
Assumption: v_i and v_d should be close to each other in the vector space if word i appears in data record d

$$\frac{v_{d1} \cdot v_i}{\|v_{d1}\|\|v_i\|} = appear(i, d1)$$
$$\frac{v_{d2} \cdot v_i}{\|v_{d2}\|\|v_i\|} = appear(i, d2)$$
$$\ldots$$

NB: $appear(i, d1) = 1$ if word i appears in data record d and 0 otherwise.

Methodology

Our task is to find the weight vector v_i for each word i, such that the similarity of v_i and v_d is close to $appear(i, d)$ as much as possible for each data record (d).

$$v_i = \min_{v_i} \sqrt{\sum_d (sim(v_i, v_d) - appear(i, d))^2}$$

Methodology

- Finding v_i equivalent to finding the optimal solution the following equation using least squares

$$\mathbf{K}' \cdot \frac{v_i}{\|v_i\|} = \mathbf{e}_i$$
$$opt(\frac{v_i}{\|v_i\|}) = (\mathbf{K}'^T \mathbf{K}')^{-1} \mathbf{K}'^T \mathbf{e}_i$$

- Once v_i is solved, we can then estimate the most appropriate words for for unseen data .

Results

Input data	
Month	Oct
Cloud Cover	11%
Precipitation	0 mm
Temperature	25° C

Output	
Word	Weight
sunny	3.908
bright	3.797
warm	2.852
lovely	2.61
moody	2.477
hot	2.3
dependable	2.093
muggy	1.978
calm	1.933
clear	1.804
autumny	1.699

Reference

- Which phrase should be used to identify an object?
- Referring expression generation: the task of selecting the content (and, to some extent, the form) of referential noun phrases in text.
  - Look at the big dog
  - Look at Fido
  - Look at it

Types of reference

- Pronoun – it, them, him, you,...
- Name – Dr Adam Smith, Adam Smith, Adam, Dr Smith
- Definite NP – the big black dog, the big dog, the black dog, the dog

Suggestion

- Use pronoun if possible
  - Referent mentioned recently
  - Pronoun is not ambiguous
- Else use name if possible
  - Shortest form which is unambiguous and stylistically allowed
- Else use definite NP
  - Shortest one, prefer basic-level words
- Only use forms seen in corpus

Aggregation

- Aggregation: the task of merging distinct representations into a single, more concise representation
- When/how should we combine phrases?
  - ◇ Your first ascent was fine. Your second ascent was fine.
  - ◇ Your first ascent was fine, and your second ascent was fine.
  - ◇ Your first ascent and your second ascent were fine.
  - ◇ Your first and second ascents were fine.

Suggestions on Aggregation

- Generally use the deepest one we can
  - Your first ascent was safe, and your second ascent was safe.
  - Your first ascent and your second ascent were safe.
  - Your first and second ascents were safe.
- Depends on how similar phrases are.
- Depends on genre (corpus)

Microplannng

- Decide how to best express a message in language
  - ◇ Essential for producing “nice” texts
- Imitating corpus works to some degree, but not perfectly
  - ◇ Currently more of an art than a science
- Key is better understanding of how linguistic choices affected readers
  - ◇ Our SumTime weather-forecast generator microplans better than human forecasters

Realisation

- Third (last) NLG stage
- Creating linear text from (typically) structured input; ensuring syntactic correctness
- Take care of details of language
  - ◇ Syntactic details
    - Eg Agreement (the dog runs vs the dogs run)
  - ◇ Morphological details
    - Eg, plurals (dog/dogs vs box/boxes)
  - ◇ Presentation details
    - Eg, fit to 80 column width

Realisation

- Problem: There are lots of finicky details of language which most people developing NLG systems don't want to worry about
- Solution: Automate this using a realiser

Syntax

- Sentences must obey the rules of English grammar
  - Specifies which order words should appear in, extra function words, word forms
- Many aspects of grammar are somewhat bizarre
- Just tell realiser verb, tense, whether negated, and it will figure out the verb group
  - (watch, future) -> will watch
  - (watch, past, negated) -> did not watch
  - Etc
- Similarly automate other "obscure" encodings of information

Morphology

In linguistics, morphology is the study of words, how they are formed, and their relationship to other words in the same language. E.g.,

- Variations of a root form of a word, e.g., prefixes, suffixes
- Inflectional morphology - same core meaning
  - plurals, past tense, superlatives, e.g., dog, dogs
  - part of speech unchanged
- Derivational morphology - change meaning
  - prefix *re* means do again: reheat, resit
  - suffix *er* means one who: teacher, baker
  - part of speech changed

Realiser

- Calculates morphological variants automatically
  - (dog, plural) -> dogs
  - (box, plural) -> boxes
  - (child, plural) -> children
  - etc
- Automatically insert appropriate punctuation for a structure
- Many possible output formats
  - Simple text
  - HTML
  - MS Word

Realiser systems

- simpleNLG – relatively limited functionality, but well documented, fast, easy to use, tested
  - ◇ Most popular, easy-to-use, programmatically controllable and extendable realisation engine.
  - ◇ Has adapted into many (western) languages: French, German, Mandarin ...
- KPML – lots of functionality but poorly documented, buggy, slow
- openCCG – somewhere in between
- Many more

Summary

Realiser

- creates linear text from (typically) structured input; ensuring syntactic correctness
- automates the finicky details of language
  - ◇ So NLG developer doesn't have to worry about these
  - ◇ One of the advantages of NLG