

## Assessing the Quality of Natural Language Text

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GI 2004

## Agenda

- Introduction and Background to Text Quality
- Text Quality Dimensions
  - Intrinsic Text Quality, Accessibility, Contextual and Representational Text Quality
- Text Quality Metrics
  - Text Quality Audit Guideline
  - Computational Metrics
- Application example

## **Introduction and Background**

- Empirical approach: Data quality -> Text quality
- Data Quality:
  - Structured data fields: numbers, names, customer address, ...
  - Correct data entries, no duplicates, referential integrity (RDBS)
  - Correct process models (data warehouse), Data Cleaning

## ■ Text Quality:

- unstructured data fields: Free text of arbitrary length
- Examples: reports, customer emails, web pages, papers, ...

## **Introduction and Background**

■ Linguistic data are ubiquitous.

■ Data Retrieval -> Information Retrieval

■ Information Retrieval Market -> NLP Market

Data Quality -> Text Quality

## **Text Quality Dimensions**

- Concept: Fitness for use, user judges whether data is fit for use, beyond accuracy.
- Basis: Data Quality Dimensions [WS96]

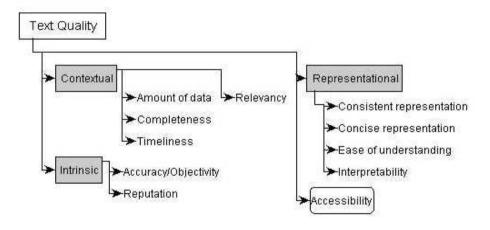
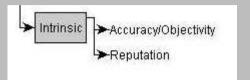


Figure 1: Text quality dimensions.

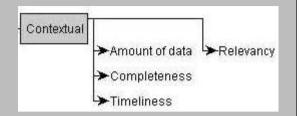
# **Text Quality Dimensions**



- Intrinsic Text Quality
  - M: No comp. to other documents content is possible.
  - H/M: Reputation very common for textual domain.
  - Example: author, institution, references, print run in research papers
    - transitive to references contained

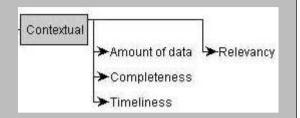
■ reputation <---> believability <---> accuracy

## **Text Quality Dimensions**



- Contextual Text Quality
  - Common Approach: Appropriate contextual parameters must be set manually.
  - Example:
    - Weather report: short, concise, no complete sentences
    - Pilot manual: restricted vocabulary
- Suitability for automatic processing
- Contextual -> Representational Text Quality

## **Text Quality Dimensions**



## Weather Report Example

Thomas Leplus, Philippe Langlais and Guy Lapalme RALI-DIRO, Université de Montréal

FPCN18 CWUL 312130

SUMMARY FORECAST FOR WESTERN QUEBEC ISSUED BY ENVIRONMENT CANADA

MONTREAL AT 4.30 PM EST MONDAY 31 DECEMBER 2001 FOR TUESDAY 01 JANUARY 2002. VARIABLE CLOUDINESS WITH FLURRIES. HIGH NEAR MINUS 7.

END/LT

FPCN78 CWUL 312130

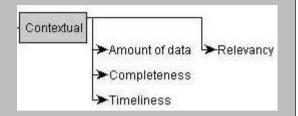
RESUME DES PREVISIONS POUR L'OUEST DU QUEBEC EMISES PAR ENVIRONNEMENT CANADA

MONTREAL 16H30 HNE LE LUNDI 31 DECEMBRE 2001 POUR MARDI LE 01 JANVIER 2002. CIEL VARIABLE AVEC AVERSES DE NEIGE. MAX PRES DE MOINS 7.

FIN/TR

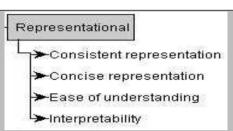
Figure 1: An example of an English weather report and its French translation.

## **Text Quality Dimensions**



- Pilot Manual Example
  - Technical Writing Guideline:
    - Be as specific and simple as possible. Use simple sentence construction. Identify nouns with specific names. Take advantage of labels on equipment diagrams. Define terms which may be unfamiliar to your reader, or leave them out. Avoid using "a lot", "very", "much", and "significantly", ... ...
    - http://research.faa.gov/aar/tech/docs/techreport/01-43.pdf
      - -New procedures are reviewed by a peer, approved by a lead writer, and proofread for grammar and typographic accuracy.
      - Vocabulary is limited to include only words found in the United States Air Force dictionary.
      - The writing process is ISO 9000 certified.

## **Text Quality Dimensions**

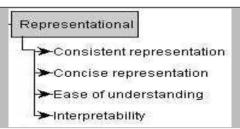


- Representational Text Quality
- Explain by Representational deficits:
  - Single Source Problems:
    - Wrong formulated data values, typing errors, different spellings of same word, co-reference problems, lexical ambiguity.
    - Wrong formulated data values<sup>3</sup>. October, 3rd of October, October 3rd.

■ Co-reference problem:  $Peter = he = my \ friend$ 

■ Lexical ambiguity: *Birne* 

# **Text Quality Dimensions**



- Representational Text Quality
  - Multi-Source Problems:
    - Homonym name conflicts (special type of lexical ambiguity)
    - Document duplicates (and identification)

## **Text Quality Metrics**

 Assessing Text Quality -> Data Cleaning <- Obtain and interpret metric values automatically.

#### ■ Problems:

Lack of methods to get at the real content of texts vs.

Content defines very important quality measures.

-> Many reservations on effective quality measures.

#### ■ Idea:

- Define Text Quality with respect to consumer, human and machine separately.
- Focus on Text Representation for classification, retrieval and IE.

## **Text Quality Metrics**

- Audit guideline: Measure inconformities: Direct observation vs. Reading the text.
- Introduce new viewpoint.
  - Condition context: (1) text to satisfy information need, (2) info contained in text, (3) info candid, (4) info can be extracted by native speaker

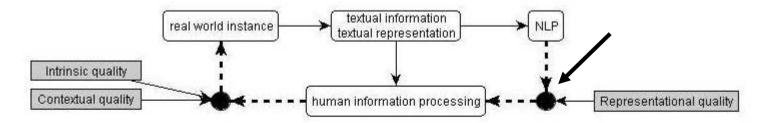
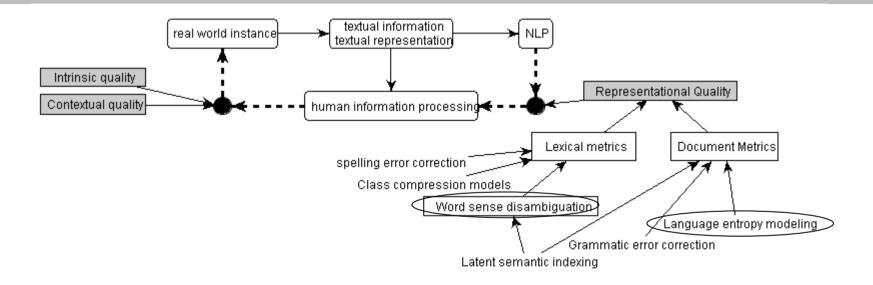


Figure 2: Text quality audit guideline.

**Computational metrics:** The base model is to define a normative state  $N^T$  on training set T in respect to the quality aspect in question. We then derive patterns  $P^S$  from new texts S, like frequencies, covariance matrices, or other parameter loads. We then compare both

- lacksquare degree of deviation  $\delta(N^T, P^S)$
- The less the degree, the better the quality.



- Spelling quality: frequency patterns (error/appearance)
- Ambiguity quality: Homonym lookup in synonym classes
- Grammatical quality: error frequen The dogs is barking.

Language Entropy Modelling

$$H(W_{1,n}) = -\sum_{w_{1,n}} P(w_{1,n}) \log P(w_{1,n})$$

- Entropy: measure of uncertainty about what a message says.
- Uncertainty can be regarded as lack in quality.
- Figure of merit to compare models: per word cross entropy

$$\frac{1}{n}H(W_{1,n}) = -\frac{1}{n}\sum_{w_{1,n}}P(w_{1,n})\log P_{Model}(w_{1,n})$$

$$H(L, P_{Model}) = -\lim_{n \to \infty} \frac{1}{n} \sum_{w_{1,n}} \log P_{Model}(w_{1,n})$$

- Language Entropy Modelling
  - The model with smallest cross entropy is best of the lot.

degree of deviation  $\delta(N^T, P^S)$ 

$$H\left(W_{1,n}\right) \leq H\left(W_{1,n}P_{Model}\right)$$

■ (Language must be *ergodic*.)

# Computational Metrics + Enhancement

- Word Sense Disambiguation + Annotating word sense
  - Automatically: Latent Semantic Indexing
  - Manually: Rely on annotation, rely on better content representation



The Semantic Web is an extension of the current web in which information is given well-defined meaning, better enabling computers and people to work in co-operation." -- *Tim Berners-Lee, James Hendler, Ora Lassila, <u>The Semantic Web, Scientific American, May 2001</u>* 

-> Linguistic Annotation for the Semantic Web



SmartWeb is based on two parallel efforts that have the

potential of forming the basis for the next generation of the Web. The first effort is the semantic Web which provides the tools for the explicit markup of the content of Web pages; the second effort is the development of semantic Web services

# **Application: Linguistic Annotation for the Semantic Web**

Example from: Paul Buitelaar and Thierry Declerck DFKI GmbH

# **Application: Linguistic Annotation for the Semantic Web**

[NP Industrie, Handel und Dienstleistungen] [VG werden] [PP in der ersten Liste] [VG aufgefuehrt], wobei [NP die in Klammern gesetzten Zahlen] [PP auf die Mutterfirmen] [VG hinweisen].

Example from: Paul Buitelaar and Thierry Declerck DFKI GmbH

## **Application: SmartWeb**



- SmartWeb: Mobile Applications of the Semantic Web
- Two parallel efforts to form basis for the next generation of the Web:
  - Provide tools for explicit markup of content of Web pages.
  - Development of *Semantic Web Services*, agents become producers and consumers of information (^= automatic NLP).

### **Conclusions**



- Data Quality dimensions suitable for Text Quality dimensions.
- Measure Text Quality for Humans and NLP separately.
- Representational Text Quality is measurable.
- Text quality for NLP traces back to questions of text representation.

■ Better text representation is the key for better text quality.

# **Reading Material**



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## **Questions**

