# Document-level Text Quality: Models for Organization and Reader Interest

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Joint work with Ani Nenkova

# People spontaneously respond to differences in writing

coherent texts from large comparations a using structure have proved useful for several model of text, production or dialog has an interest production or dialo

#### http://www.publishersweekly.com

### The Top 10 Most Difficult Books



"Finnegans Wake is long, dense, and linguistically knotty, yet hugely rewarding, if you're willing to learn how to read it..."

#### http://www.cnn.com

"My Faith: Why I don't sing the 'Star Spangled Banner'"

"What a poorly written article. Strays off topic and hardly even addresses the point of the article.

The only brief mention of why they don't play the national anthem is that they believe in church and state. This just was one long rant about his religion."

#### http://www.vocabula.com



**hubris** (HYOO-bris) — excessive pride or self-confidence; arrogance.

This word is striking, bold and its meaning is completely unexpected.

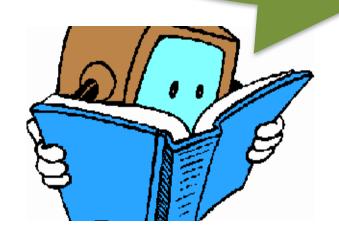
dodecahedron (doh-dek-ah-HEE-dren) — any polyhedron having twelve plane faces.

It's almost musical.

# **Text Quality Prediction**

Can we teach computers to make similar judgements?

This article is well-written. Next one..



- O How to formulate the task?
- Get suitable data with distinctions
- Find correlates in text

# Why do we care?

- Information retrieval, article recommendation
  - All articles are not of the same quality
  - Can filter by quality in addition to relevance
- Authoring support, educational assessment
  - Automatic assessment is cheap, consistent and quick
  - Spelling and grammar correction are commercially successful
- Text generation systems
  - Systems can understand how to generate coherent text
  - Can evaluate system output

### This talk

- Defining text quality and creating a corpus of overall article ratings
  - Large scale realistic sample of writing differences
- Two models
  - A model for organization using syntax patterns
  - A model for reader interest
- Document-level quality prediction
  - In contrast to spelling and grammar
  - Often not a binary, correct/in-correct distinction

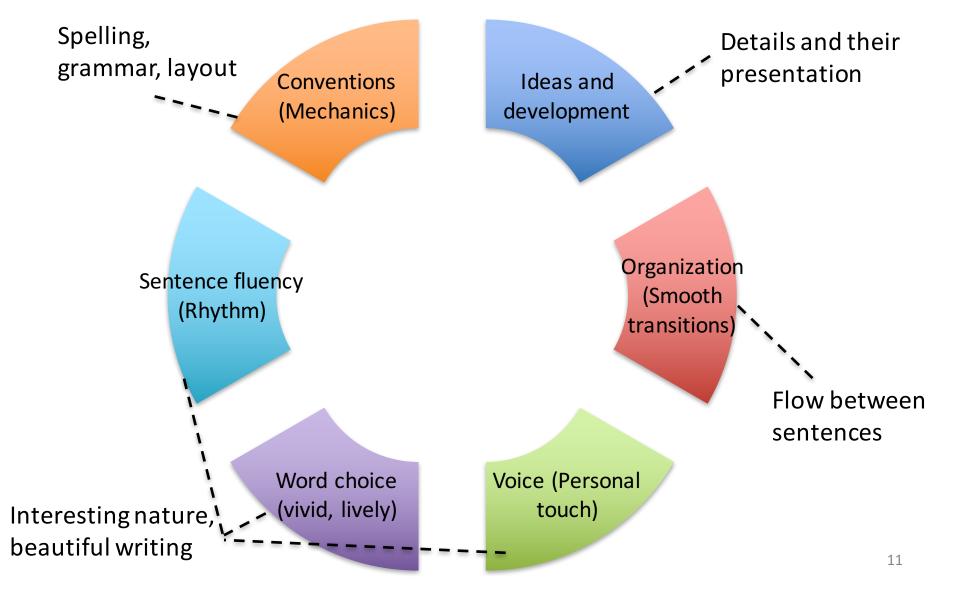
### >> Defining Text Quality

- Aspects of quality
- Who is the audience?

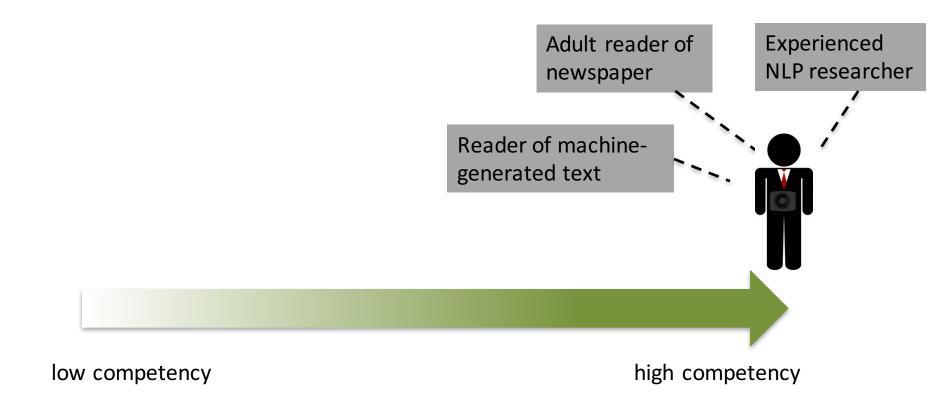
## Aspects of quality

We adopt a definition from the education field

## Six Traits [Spandel 2004]



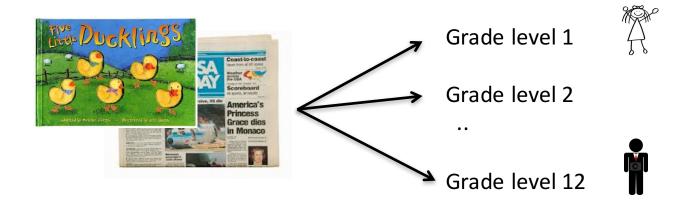
### Audience for text quality – An expert



Increased focus on linguistic properties of the text

### Relationship to readability

Readability has a strong focus on comprehension



- Audience distinctions
  - child vs. adult, novice vs. expert, cognitive disability or not

### >> A Corpus for Document-level Quality

Louis & Nenkova, Discourse and Dialogue, 2013

### The New York Times

**Science** 

Thursday, April 7, 2011

#### As Dinosaurs Waned and Mammals Rose, the Lowly Louse Kept Pace

By NICHOLAS WADE

Lice are expert evolvers, and a new family tree of lice stretches so far back that the host of the first louse would have been a dinosaur.

### Science journalism: example snippet

Sarah Lewis is fluent in firefly.

On this night she walks through a farm field in eastern Massachusetts, watching the first fireflies of the evening rise into the air and begin to blink on and off.

Dr. Lewis, an evolutionary ecologist at Tufts University...

## Category 1: VERY GOOD articles

 Seed set = 63 New York Times articles that appeared in the Best American Science Writing series

- We choose only the NYT articles
  - We use the NYT Corpus to expand our category
  - Normalize for differences in writing due to source

# Topics in the seed set

| Tag                          | Appearance |
|------------------------------|------------|
| Medicine and Health          | 22         |
| Space                        | 14         |
| Physics                      | 10         |
| Biology and Biochemistry     | 8          |
| Genetics and Heredity        | 8          |
| Archaeology and Anthropology | 7          |
| 0 010                        |            |
| Computers and the Internet   | 4          |

### Expanding the VERY GOOD set

 Assume: ~40 authors of the seed set are excellent writers

- Other articles from the NYT written by the same authors
  - which are research related
  - during the same 10 year period
  - on similar topics
  - similar lengths

### Category 2: TYPICAL writing in the NYT

 Other science articles around the same time, but not written by the popular authors

#### The general corpus:

| Category  | Total Articles |
|-----------|----------------|
| VERY GOOD | 3,530          |
| TYPICAL   | 20,242         |

### A topic-paired corpus

- The general categories mix different topics
  - geography, biology, astronomy, linguistics...
- But an IR system compares articles on the same topic

- For each VERY GOOD article, get 10 most similar TYPICAL articles (based on the content)
- Enumerate all pairs of (VERY GOOD, TYPICAL)

• 35,300 pairs

### Two quality prediction tasks

2 categories GOOD (~3500) TYPICAL (~3500) Topically similar pairs <VERY GOOD, TYPICAL>~35,000 pairs

`Same-topic'

— which article in the pair is the VERY GOOD one?

### Properties of the dataset

Distinguishes average writing from very good

- Allow to focus on aspects such as beautiful writing
  - Less likely to have spelling and grammar errors

- Large scale and realistic sample of writing differences
  - Previous work often used machine generated text or artificially manipulated text

# >> Predicting organization quality

Louis & Nenkova, EMNLP 2012



# Some sequences of sentence types convey the overall purpose better

Motivation

Solving X is useful for many applications.

Introduce approach

We present a new approach to address X.

Results

Results show that our method works well.

### Intentional structure of an article

Every text has a purpose that the author wishes to convey

 Influential early theories discuss it at length
 [Grosz & Sidner 1986]

 Particularly for academic writing, it is popular to see articles as a sequence of intentions

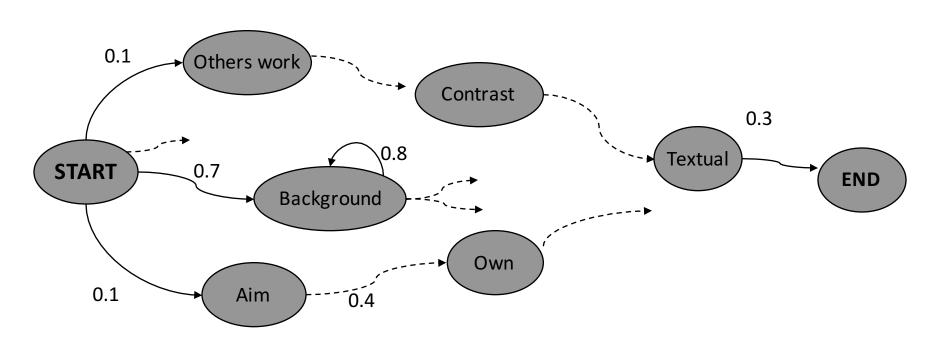
[Swales 1990, Teufel 2000]



### Oracle model of intentional structure

Using manual annotations of intentions on ACL articles
 [corpus by Teufel, 2000]

#### Markov Chain on Introduction sections



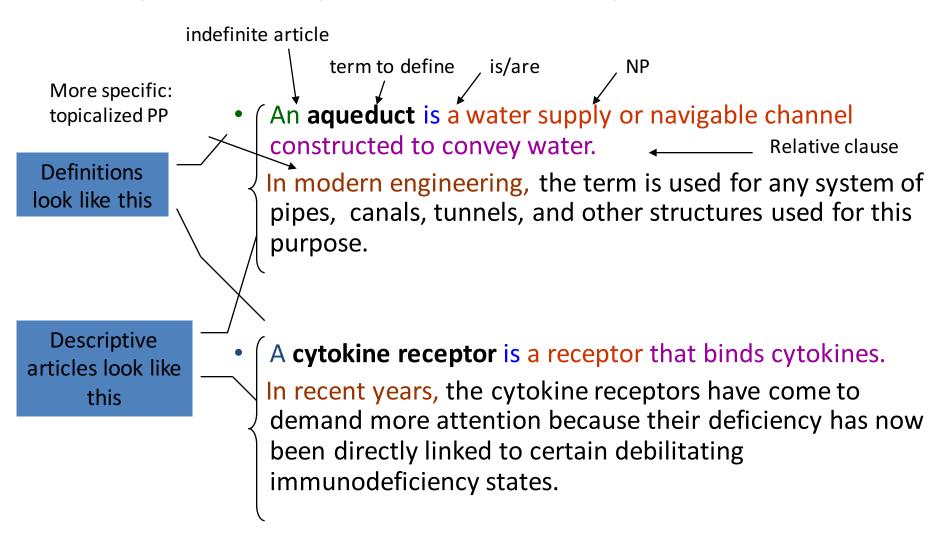
### Main idea of the work

 Annotating sentence types is hard. Pre-defining the set of sentence types is harder

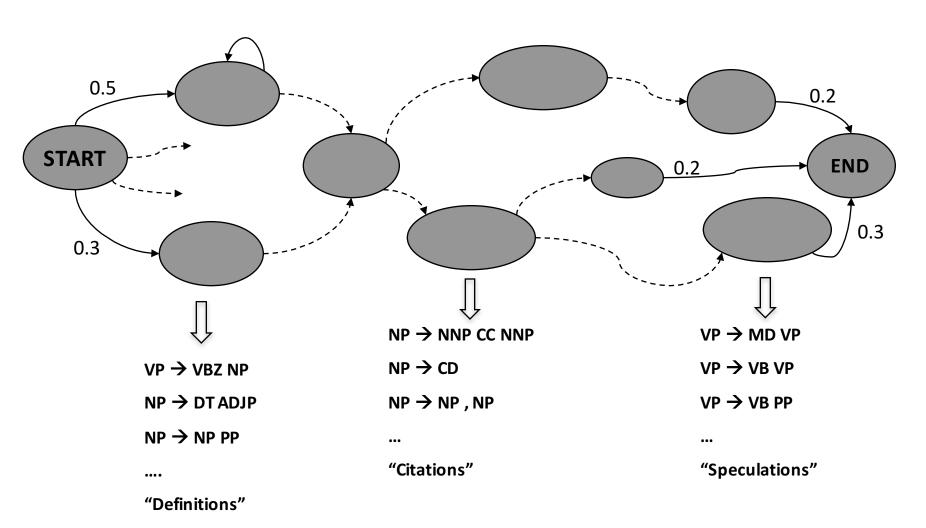
Assume

Syntax ~ rough proxy for sentence type

### Syntactic patterns in explanations



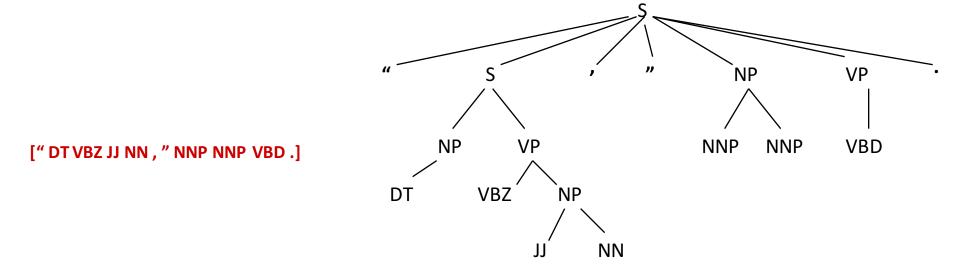
## Syntax-based HMM model



<sup>\*</sup> Uses grammatical productions

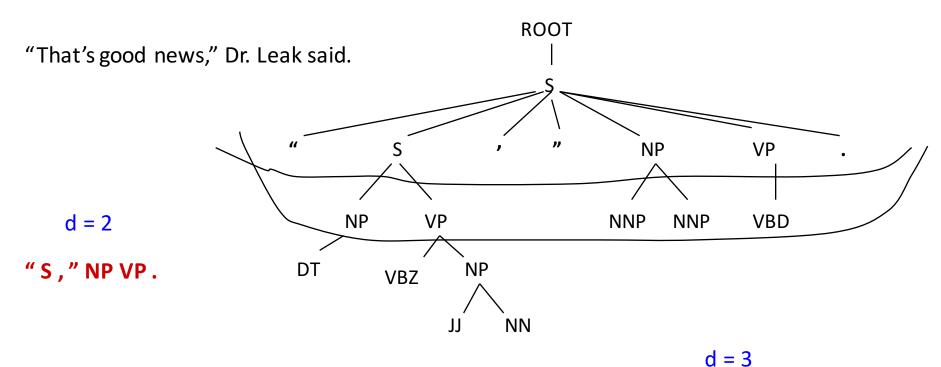
### A second model: based on *d*-sequences

- More information about adjacent constituents
- A POS tag sequence loses all abstraction



- D-sequence
  - control abstraction using a parameter "depth" (d)

### Step 1 – depth cutoff

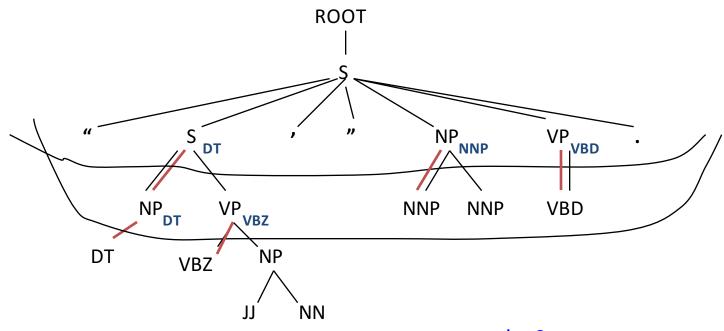


Choose a depth d

Terminate tree at d

Read off *new* leaves from left to right

### Step 2: Node augmentation



For phrasal nodes in d-sequence,

- Annotate with left most leaf in full tree

$$d = 2$$

$$"S_{DT}, "NP_{NNP} VP_{VBD}.$$

$$d = 3$$

$$"NP_{DT} VP_{VBZ}, "NNP NNP VBD.$$

## Evaluation task on academic writing

- ACL anthology corpus
  - abstract, introduction, related work

- Approximate distinction for organization quality
  - Original article → well-organized
  - Random permutation of original → poorly-organized
  - Create pairs <original, permutation?</p>
- Task: identify the original version in the pair
  - Baseline 50% accuracy

### Summary of results on academic writing

- Correct = higher likelihood for original article
  - versus permuted article
- D-seq model

| ACL conference | Accuracy |
|----------------|----------|
| Abstract       | 62.9     |
| Introduction   | 68.8     |
| Related work   | 72.7     |

Baseline = 50%

# Do sentence types distinguish VERY GOOD and TYPICAL science news?

Create the HMM on VERY GOOD training articles

- Get likelihood and most likely state sequence for a new article
  - Compute features based on these
- A classifier is trained to predict the VERY GOOD article

### Results on our corpus

**Any Topic**: Given an article, is it "VERY GOOD" or "TYPICAL"?

| System            | Accuracy |
|-------------------|----------|
| Baseline (random) | 50%      |
| HMM-productions   | 61%      |

- 10 fold cross validation results
- SVM classifier

**Same Topic**: Given a pair of articles on the same topic, which one is "VERY GOOD"?

| System            | Accuracy |
|-------------------|----------|
| Baseline (random) | 50%      |
| HMM-productions   | 63%      |

# >> Predicting reader interest

Louis & Nenkova, TACL 2013

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# Predicting interest: A new task

- A lot of work on identifying what is wrong with a text
  - Spelling mistakes, grammar errors, incoherent writing
- It is not known how to characterize writing that is engaging, interesting and nice

# Approach to feature development

- Focus on interpretable features
  - Only 41 features
  - Each feature is a composite one: indicates an aspect directly
  - Linguistically interesting
- Confirm that features represent the intended aspect
  - Tune by checking feature values on random snippets of text

# 1. Unusual words and phrases

## Is the phrasing and language use unique?

- Word-based
  - high perplexity under a phoneme n-gram model
  - Eg: 'undersheriff', 'powwow', 'chihuahua', 'qipao'

- Word pairs--based
  - adjective-noun, noun-noun, adverb-verb, subject-verb pairs
  - perplexity under a language model
  - Eg: 'plasticky woman', 'so-called superkids'

## 2. Visual nature

## Is there scene setting?

- Creating a large lexicon of visual terms
  - Source: an image-tagged corpus
  - Large source of potentially visual words, but noisy

- Create LDA-based topics on the tag set
  - Use the manual MRC terms to filter out non-visual topics

grass, mountain, green, hill, blue, field, sand... round, ball, circles, logo, dots, square, sphere... silver, white, diamond, gold, necklace, chain...

# Human interest and text structure

### 3. Use of people in the story

Does the story revolve around a person?

animacy information from NEs, pronouns, ngram patterns

## 4. Sub-genre

Is the article is a narrative, interview or dialog

 Eg: narrative score ~ past tense verbs, pronouns, proper names

# Sentiment and Research

#### 5. Affect

Is there an emotional angle to the story?

using sentiment word dictionaries

#### Research content

How much explicit research description is present?

using a hand-built dictionary of research words

# How the features vary in a random sample of very good and typical articles (t-test)

#### **Higher values in VERY GOOD set**

- ✓ Visual words in beginning and end of articles
- ✓ Unusual words and phrases

- ✓ Sentiment words, negative polarity
- ✓ Research words

- X Total visual words
- $\times$  Animacy counts
- X Narrative, interview or dialog format

## Accuracies on the two tasks

**Any Topic**: Given an article, is it "VERY GOOD" or "TYPICAL"?

| System                       | Accuracy |  |
|------------------------------|----------|--|
| Baseline (random)            | 50%      |  |
| Interesting-science features | 75%      |  |

- 10 fold cross validation results
- SVM classifier

**Same Topic**: Given a pair of articles on the same topic, which one is "VERY GOOD"?

| System                       | Accuracy |  |
|------------------------------|----------|--|
| Baseline (random)            | 50%      |  |
| Interesting-science features | 68%      |  |

# Combining interest with other aspects

| Feature set         | any topic | same topic |
|---------------------|-----------|------------|
| Interesting science | 75.3      | 68.0       |

Genre-specific measures are stronger than generic ones

Different
aspects of
writing have
complementary
strengths

# Conclusions

- Text quality is an interesting and challenging task
- More success on the topic recently
  - application to novels, tweets, essays

- Future work
  - A lot to be done in terms of formalizing the tasks, collecting data, models and evaluation
  - Transferring the knowledge to generating texts

# Thank you!