Digital Libraries

Computational Literary Analysis, Duplicate and Plagiarism Detection

Week 9

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Outline

o Literary Analysis

- Authorship detection
- Genre classification

o Duplicate Detection

Web pages

o Plagiarism Detection

- In text
- In programs



The Federalist papers

 A series of 85 papers written by Jay, Hamilton and Madison

 Intended to help persuade voters to ratify the US constitution



Disputed papers of the Federalist

- Most of the papers have attribution but the authorship of 12 papers are disputed
 - Either Hamilton or Madison
- Want to determine who wrote these papers
 - Also known as textual forensics



Hamilton



Madison

Wordprint and Stylistics

 Claim: Authors leave a unique wordprint in the documents which they author

 Claim: Authors also exhibit certain *stylistic patterns* in their publications

Feature Selection

o Content-specific features (Foster 90)

key words, special characters

o Style markers

- Word- or character-based features
 o length of words, vocabulary richness
- Function words (Mosteller & Wallace 64)

Structural features

- Email: Title or signature, paragraph separators (de Vel et al. 01)
- Can generalize to HTML tags
- To think about: artifact of authoring software?

Bayes Theorem on function words

o M & W examined the frequency of 100 function words

Frequency	Hamilton	Madison	
0	.607	.368	
1	.303	.368	
2	.0758	.184	

 Used Bayes' theorem and linear regression to find weights to fit for observed data

• Sample words:

as	do	has	is	no	or	than	this
at	down	have	it	not	our	that	to
be	even	her	its	now	shall	the	up

A Funeral Elegy and Primary Colors

"Give anonymous offenders enough verbal rope and column inches, and they will hang themselves for you, every time" – Donald Foster in *Author Unknown*

- A Funeral Elegy: Foster attributed this poem to W.S.
 - Initially rejected, but identified his anonymous reviewer
- Forster also attributed *Primary Colors* to Newsweek columnist Joe Klein

• Analyzes text mainly by hand

Foster's features

- Very large feature space, look for distinguishing features:
 - Topic words
 - Punctuation
 - Misused common words
 - Irregular spelling and grammar

o Some specific features (most compound):

- Adverbs ending with "y": talky
- Parenthetical connectives: ..., then, ...
- Nouns ending with "mode", "style": crisis mode, outdoor-stadium style

Typology of English texts

Biber (89) typed different genres of texts

- Five dimensions ...
 - 1. Involved vs. informational production
 - 2. Narrative?
 - Explicit vs. situation-dependent
 - 4. Persuasive?
 - 5. Abstract?

... targeting these genres

- 1. Intimate, interpersonal interactions
- 2. Face-to-face conversations
- 3. Scientific exposition
- 4. Imaginative narrative
- 5. General narrative exposition

Features used (e.g., Dimension 1)

 Biber also gives a feature inventory for each dimension 	35 30 25	Face to face conversations			
THAT deletion	20	Personal Letters Interviews			
Contractions	15				
BE as main verb WH questions	10				
1 st person pronouns	5	Durana da sa sa ka s			
2 nd person pronouns	о	Prepared speecnes			
General hedges +	-5	General fiction			
Nouns _ Word Length	-10	Editorials			
Prepositions	-15	Academic prose; Press reportage			
Type/Token Ratio	-20	Official Documents			
CS 5244 - C	omputationa	l			
2005 Document Analysis					

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Discriminant analysis for text genres

• Karlgren and Cutting (94)

- Same text genre categories as Biber
- Simple count and average metrics
- Discriminant analysis (using SPSS software)
- 64% precision over four categories
- Adverb Some count features
 - Character
 - Long word (> 6 chars)
 - Preposition
 - 2nd person pronoun
 - "Therefore"
 - 1st person pronoun
 - "Me"
 - "T"
 - Sentence

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- Words per sentence
- Characters per sentence
- Words per sentence
 Characters per word
 Characters per sente
 Type / Token Ratio

Genre vs. Subject (Lee & Myaeng 02)

- Genre: style and purpose of text
- Subject: content of text

What about the interaction between the two?

Study found that certain genres overlap signficantly in subject vocabulary

- So, want to use terms that cover more subjects represented by a genre
- Do this by selecting terms that:
 - 1. Appear in a large ratio of documents belonging to the genre
 - 2. Appear evenly distributed among the subject classes that represent the genre
 - 3. Discriminate this genre from others

Putting the constraints together

Document Frequency Ratios (coverage of term to genre or genre+subject)

$$DFR_g(t) = \frac{df_{g,t}}{df_g}$$

Use these to define the weight

$$W_g(t) = DFR_g(t) * (1 - \sigma)$$

What are some negative aspects of this approach?

Where σ is a penalty ("deviation") factor for terms that are spread widely over different subjects

$$\sigma = \sqrt{\frac{\sum_{|S|} (DFR_g(t) - DFR_{g,s}(t))^2}{|S|}}$$

 $DFR_{g,s}(t) = \frac{df_{g,s,t}}{df_{g,s}}$

In summary...

Genre and authorship analysis relies on highly frequent evidence that is portable across document subjects.

Contrast with subject/text classification which looks for specific keywords as evidence.

References:

- Mosteller & Wallace (63) *Inference in an authorship problem*, J American Statistical Association 58(3)
- Karlgren & Cutting (94) *Recognizing Text Genres with Simple Metrics Using Discriminant Analysis, Proc. of COLING-94.*
- *de Vel, Anderson, Corney & Mohay (01) Mining Email Content for Author Identification Forensics,* SIGMOD Record
- Foster (00) Author Unknown. Owl Books PE1421 Fos
- Biber (89) *A typology of English texts,* Linguistics, 27(3)
- Lee and Myaeng (02)

To think about...

- The Mosteller-Wallace method examines function words while Foster's method uses key words. What are the advantages and disadvantages of these two different methods?
- What are the implications of an application that would emulate the wordprint of another author?
- What are some of the potential effects of being able to undo anonymity?



Water Break



See you in five minutes!

I will hold a short tutorial for HW #2 at the end of class today.

Copy detection

Duplicate detection characteristics

o Plagiarism

- copies intentionally
- may obfuscate
- target and source relation

o Self-plagiarism*

- copy from one's own work
- Often to offer for background of work in incremental research

- o (near) Clone/duplicate
 - same functionality in code / citation data
 - but in different modules by different developers
- Fragment
 - web page content generated by content manager
 - interferes with spiders' re-sampling rate

Signature method

- 1. Register signature of authority doc
- Check a query doc against existing signature
- 3. Flag down very similar documents

Some design choices have to be made:

- How to compute a signature
- How to judge similarity between signatures

Effect of granularity

Divide the document into smaller chunks document – no division sentence window of *n* words

- Large chunks
 - Lower probability of match, higher threshold
- o Small chunks
 - Smaller number of unique chunks
 - Lower search complexity



Signature methods

For text documents

- o Checksum
- o Keywords
- N-gram (usually character) inventory
- Grammatical phrases

For source code

- Words, characters and lines
- Halstead profile (Ignores comments)
 - Operator histogram
 - e.g., frequency of each type sorted
 - Operand histogram

Distance calculations

Calculate distance between p_1 , p_2

- VSM: L₁ distance $\Sigma_f |P_{f1} P_{f2}|$
- VSM: L₂ Euclidean distance $(\Sigma_f | P_{f1} P_{f2} |^2)^{1/2}$
- Weighted feature combinations
- For text features, can use edit distance
 - Calculate using dynamic programming

Detect and flag copies

- Assume top n% as possible plagiarisms
- Use a tuned similarity threshold
- Other way: do tuning on supervised set (learn weights for features: Bilenko and Mooney)

What are some problems with these approaches?

Subset problem

- Problem: If a document consists is just a subset of another document, standard VS model may show low similarity
 - Example: cosine (D₁,D₂) = .61
 D₁: <A, B, C>,
 D₂: <A, B, C, D, E, F, G, H>
- Shivakumar and Garcia-Molina (95): use only *close* words in VSM
 - Close = comparable frequency, defined by a tunable ε distance.

R-measure: amount repeated in other documents (Khmelev and Teahan)

• Normalized sum of lengths of all suffixes of the text repeated in other documents

$$R^{2}(T \mid T_{1}, \dots T_{m}) = \frac{2}{l(l+1)} \sum_{i=1}^{l} Q(T[i..l] \mid T_{1}, \dots T_{m}),$$

where $Q(S|T_1...T_n) = \text{length of longest prefix of } S$ repeated in any one document

- Computed easily using suffix array data structure
- More effective than simple longest common substring



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R-measure example

 $T = cat_sat_on$ $T1 = the_cat_on_a_mat \quad \frac{2}{l(l+1)} \sum_{i=1}^{l} Q(T[i..l] | T_1, ..., T_m),$ $T2 = the_cat_sat$

CS 5244 - Computational

Document Analysis

Computer program plagiarism

- Use stylistic rules to compile fingerprint:
 - Commenting
 - Variable names
 - Formatting
 - Style (e.g., K&R)
- Use this along with program structure
 - Edit distance

What about hypertext structure in the web?

```
/*
 * concatenate s2 to s1 into s3.
 * Enough memory for s3 must already be
            allocated. No checks !!!!!!
 */
mysc(s1, s2, s3)
            char *s1, *s2, *s3;
{
    while (*s1)
            *s3++ = *s1++;
    while (*s2)
            *s3++ = *s2++;
}
```

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Design-based methods

- Idea: capture syntactic and semantic flow rather than token identity (for source code)
- Replace variable names with IDs correlated with symbol table and data type
- Decompose each *p* into regions of
 - sequential statements
 - conditionals
 - looping blocks recurse on these
- Calculate similarity from root node downwards





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Document Analysis

Defining fragments

- Base case: each web page is a fragment
- Inductive step: each part of a fragment is also a fragment if
 - Shared: it is shared among at least n other fragments (n > 1) and is not subsumed by a parent fragment
 - Different: it changes at a different rate than fragments containing it

Conclusion

- Signature-based methods common, design-based assumes domain knowledge.
 - The importance of granularity and ordering changes between domains
- o Difficult to scale up
 - Most work only does pairwise comparison
 - Low complexity clustering may help as a first pass

References

- Belkouche *et al.* (04) *Plagiarism Detection in Software Designs,* ACM Southeast Conference
- Shivakumar & Garcia-Molina (95) *SCAM: A copy detection mechanism for digital documents*, Proc. of DL 95.
- Bilenko and Mooney (03) Adaptive duplicate detection using learnable string similarity measures, Proc. of KDD 03.
- Khmelev and Teahan (03) A repetition based measure for verification of text collections and for text categorization, Proc. SIGIR 03
- Ramaswamy et al. (04) Automatic detection of fragments in dynamically generated web pages, Proc. WWW 04.

To think about...

- How to free duplicate detection algorithms from needing to do pairwise comparisons?
- What size chunk would you use for signature based methods for images, music, video? Would you encode a structural dependency as well (ordering using edit distance) or not (bag of chunks using VSM) for these other media types?