Measuring the Structural Similarity of Semistructured Documents Using Entropy

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Introduction

- XML is everywhere ...
- In traditional IR detecting similarities used widely:
 - for querying
 - for clustering
- Consequently, lots of similarity measures for text documents

Introduction(2)

New challenges with semistructured documents:

- measuring structural similarity
- semistructured documents show great structural diversity
- Measuring structural similarity used for:
 - entity resolution in data cleaning
 - clustering documents before extracting DTD or schema information
 - integrating heterogeneous data sources
 - as a query tool for inexperienced users (query-by-example)

Measuring Entropy

- Bennet et al. introduced concept of universal information metric
- Based on Kolmogorov complexity:
 - given data object x, Kolmogorov complexity K(x) is the length of shortest program that outputs x
- Generalized form is conditional Kolmogorov complexity K(x|y):
 - length of the shortest program with input y that outputs x

Information Distance

Similarity of two data objects can be measured by normalized information distance:

$$NID(x,y) = \frac{\max(K(x|y), K(y|x))}{\max(K(x), K(y))}$$

- Has some nice properties: it's "almost" a metric, lower bound for admissible distances
- So what's the catch?

Information Distance(2)

- Unfortunately, Kolmogorov complexity is not computable in general
- However, can be approximated by compression (Cilibrasi and Vitányi):

$$NCD(x,y) = \frac{C(xy) - \min(C(x), C(y))}{\max(C(x), C(y))}$$

Measuring Structural Similarity

- Just compressing XML files does not get the job done
- Extract structural information first:
 - Tags: list element/attribute names in document order
 - Pairwise: like tags, but with names of parents
 - Path: like tags, but with full path to root
 - Family order: family-order traversal of document
- Except Path, all extractions can be done in linear time

Measuring Structural Similarity(2)

- After extracting structural information, we use
 - *NCD* with gzip
 - Ziv-Merhav crossparsing

to come up with similarity measure

Can be done in linear time (with suffix trees)

Competitors

- Tree-editing distance (Nierman and Jagadish):
 - measuring the minimum editing distance
 - five different edit operations: relabel, insert & delete node, insert & delete (sub-)tree
 - Quadratic runtime

Competitors(2)

Discrete Fourier Transformation (Flesca et al.):

- encode XML document as a time series
 - rotate document by 90°, interpret indentations as time series
- use DFT transform to compute similarity
- Runtime: $N \log N$ (N size of larger document)

Competitors(3)

- Path shingles (Buttler)
 - extract structural information using the Full Path variant
 - compute a hash value h_j for each path
 - a shingle of width w is the combination of w consecutive hash values
 - compute similarity between two documents using Dice coefficient on the two sets of shingles
 - Original version is not linear, can be made linear by using different extraction technique

Clustering Quality

- Measure quality of similarity measure by clustering
- We used hierarchical agglomerative clustering
- Quality expressed in number of misclusterings in dendrogram



Document Collections

- We used three different document collections for experimental evaluation:
 - Real data sets: SIGMOD record, INEX 2005, music sheets encoded in XML
 - Synthetically generated data sets from the DFT paper
 - Own synthetically generated data sets, varying:
 - element names
 - element frequencies
 - element positions
 - element depths

Overall Results

tree-edit	15.3%	
DFT		
direct ML	22.4%	
pairwise ML	19.7%	
Shingles		
tags	20.4%	
pairwise	17.8%	
full path	15.3%	

gzip	
simple	26.1%
tags	17.7%
pairwise	20.8%
full path	16.9%
family order	18.9%
Ziv-Merhav	
tags	11.7%
pairwise	13.8%
full path	11.3%
family order	10.6%

More Detailed Results

- Different methods have different strengths and weaknesses:
 - tree-edit: generally good, has problems with largely varying document sizes
 - DFT: good at frequencies, bad at element names, position, and depth
 - gzip/Ziv-Merhav: bad at frequencies, good at element names, position, and depth
- DFT and gzip/Ziv-Merhav are complementary to each other; idea: combine them

Hybrid Version

Hybrid (DFT/Ziv-Merhav)		
pairw. ML/tags	8.8%	
pairw. ML/pairw.	12.4%	
pairw. ML/path	9.7%	
pairw. ML/family	21.4%	

- Clustering performance becomes even better (except family order)
- Hybrid approach does not have linear run time

Conclusion and Outlook

- Our approach totally different to previous approaches
- Can be done in linear time (important for large document collections)
- Possible future work:
 - more sophisticated ways of encoding document structure?
 - different entropy measure better suited for structural information?

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