CS5560 Knowledge Discovery and Management

Problem Set 3 June 19 (T), 2017

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Class ID:

Information Retrieval (Text Mining) with TF-IDF

Consider the following three short documents

Doc #1:

The researchers will focus on computational phenotyping and will produce disease prediction models from machine learning and statistical tools.

Doc #2:

The researchers will develop tools that use Bayesian statistical information to generate causal models from large and complex phenotyping datasets.

The researchers will build a computational information engine that uses machine learning to combine gene function and gene interaction information from disparate genomic data sources.

First remove stop words and punctuation; detect manually multi-word terms (using N-Gram or POS Tagging/Chunking); parse manually the documents and select the terms from the given 3 documents and created the dictionary (list of terms),

b) Create the document vectors by computing TF-IDF weights. Show how to compute the TF-IDF No el time weights for terms. For each form of weighting list the document vectors in the following formal

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After stop words and functuation removal :-Doc 1 ? Researchers focus computational phenotyping preduce disease prediction models [machine learning] (Startical foods) - Using N Grams

Doc 2: Researchers develop tools Bayesian stastical information generale council models large complex phenotyping datasets.

Doc 3: Researchers build computational information ongline [machine learning] combine function gene interaction information disparate genomic gene interaction information disparate genomic

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