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Unfortunately, ANLS subproblems are not unique as there exists scaling and permutation matrices $X \in \Re^{kxk}$ which represent scaling and permutation that satisfy $||\mathbf{A} - \mathbf{W}\mathbf{H}||_F = ||\mathbf{A} - \mathbf{W}\mathbf{X}\mathbf{X}^{-1}\mathbf{H}||_F$ (Kim, 2006).

Outline

-Introduction + definition

-cost functions: Euclidian distance, Frobinius norm, KL divergence, Renyi's divergence. Can you construct a situation in which certain norms are better than others?

- -update rules: multiplicative update, ALS method, gradient methods
- -computational comparison: flop counts, accuracy, size of inputs
- -applications to calculating metagenes

Introduction

This report introduces the framework for parts-based representations using NMF and focuses on the algorithms and numerical aspects of computation.

definition For a nonnegative matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$, select a low-rank approximation of size k such that there are two nonnegative matrices $\mathbf{W} \in \mathbb{R}^{m \times k}$ and $\mathbf{H} \in \mathbb{R}^{k \times n}$ which minimizes a function such as

$$f(\mathbf{W}, \mathbf{H}) = \frac{1}{2} ||\mathbf{A} - \mathbf{W}\mathbf{H}||_F^2$$

Other commonly used objective functions include Euclidian distance and Kullback-Leibler (KL) divergence. KL can be extended to a more general information-based framework using Renyi's divergence. (Devarajan, 2005). Here, a single parameter α is used to represent a continuum of distance measures and KL airises as a special case as $\alpha \to 1$.

$$KL(V||WH) = \sum_{ij} [V_{ij} \log \frac{V_{ij}}{(WH)_{ij}} - V_{ij} + (WH)_{ij}]$$

more text

Fundamental Algorithms

One of the first and most widely adopted algorithms for NMF is the multiplicative update rule. This takes the general form:

Data: Input data matrix: $\mathbf{A} \in \mathbb{R}^{\mathbf{mxn}}$ Result: nonnegative factorization of \mathbf{A} using \mathbf{k} components, creating matrices $\mathbf{W} \in \mathbb{R}^{mxk}$ and $\mathbf{H} \in \mathbb{R}^{kxn}$ initialization; $\mathbf{W} \leftarrow \text{random dense } (\mathbf{m} \times \mathbf{k}) \text{ matrix}$ $\mathbf{H} \leftarrow \text{random dense } (\mathbf{k} \times \mathbf{n}) \text{ matrix}$ for i = 1 to maxiter do $\begin{vmatrix} \mathbf{H} = \mathbf{H}. * (\mathbf{W}^{\mathbf{T}} \mathbf{A})./(\mathbf{W}^{\mathbf{T}} \mathbf{W} \mathbf{H}) \\ \mathbf{W} = \mathbf{W}. * (\mathbf{A} \mathbf{H}^{\mathbf{T}})./(\mathbf{W} \mathbf{H} \mathbf{H}^{\mathbf{T}}) \end{vmatrix}$ end Algorithm 1: multiplicative update

Often the requires O(mnk) work per iteration

Figure 1: A picture of a gull.

