Title: Novelty Detection in Martian Geology Using Advanced High-Dimensional Tensor Decomposition Methods

Introduction

Write an introduction to a paper that

Alternate applications

* Other image sets
  + Eg. CCTV cameras for anomaly detection, temperature sensor images, etc.
* Signal data sets for anomaly detection
  + Signals needs to be segregated into normal and non-normal sets.

Methodology <section>

Data collection and pre-processing

* Load images associate with typical or novel labels
* Each image set contains six 64x64 grayscale image
* 11,114 sets of non-novel images = total of 66,684 images
* 430 novel images sets = total of 2580 images
  + Novel images and its type are identified by an expert.
  + Several types of novel images
    - DRT spot
    - Dump pile
    - Broken rock
    - Drill hole
    - Meteorite
    - Vein
    - Float rock
    - Bedrock

Tensor decomposition

* CP decomposition
* Tucker decomposition

Model selection and training

* SVM
* Autoencoder neural networks

Model evaluation

* Evaluate detection accuracy on the novel/anomalous sets

Threshold selection

* Select the top performing decomposition threshold that optimizes prediction accuracy with run time performance.

Model deployment

* Document results for publishing
* Recommendations for further research

Limitations

* Not all training images are used for this study due to processing and storage limitations.
* The provided training dataset is approximately 1.7GB in size and tensor processing images of this size would need resources beyond what is locally available.

Prior studies:

This study builds on top of the study published by Kerner, Wagstaff, Bue, Wellington, Jacob, Horton, Bell, Kwan, and Amor with title < Comparison of novelty detection methods for multispectral images in rover-based planetary exploration missions> and the following related works.

Principal Component Analysis (PCA): Uses reconstruction error from principal subspace as a novelty score.

* Kwak (2008), Chandola et al. (2009), Toivola et al. (2010), Wagstaff et al. (2013), Xiao et al. (2013), Jablonski et al. (2015).

Autoencoders: Neural networks trained to minimize reconstruction error for typical examples; score novelty using reconstruction error.

* Hinton and Salakhutdinov (2006), Japkowicz et al. (1995), Thompson et al. (2002), Williams et al. (2002), Manevitz and Yousef (2007), Xiong and Zuo (2016), Richter and Roy (2017), Zhou and Paaenroth (2017), Kerner et al. (2019).

Variational Autoencoders & GANs: Proposed for complex data relationships and novelty detection.

* An and Cho (2015), Park et al. (2018), Goodfellow et al. (2014), Antipov et al. (2017), Dong et al. (2018), Schlegl et al. (2017), Akcay et al. (2018), Zenati et al. (2018b).

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Yes, it is possible for Tucker decomposition to produce highly accurate predictions while CP decomposition produces highly inaccurate predictions. This difference in performance can be attributed to several factors inherent to the nature of each decomposition method and the structure of the data:

**Key Differences Between Tucker and CP Decomposition**

1. **Model Complexity**:
   * **Tucker Decomposition**: Tucker decomposition is more flexible and can capture more complex interactions within the data by decomposing the tensor into a core tensor and factor matrices. This flexibility allows Tucker decomposition to model data with varying levels of complexity more effectively.
   * **CP Decomposition**: CP decomposition represents the tensor as a sum of rank-one tensors. While it is simpler and requires fewer parameters, it might not capture complex structures in the data as effectively as Tucker decomposition.
2. **Rank Selection**:
   * **Tucker Decomposition**: Allows for different ranks in each mode, which can be tuned independently to best capture the underlying structure of the data.
   * **CP Decomposition**: Uses a single rank for the entire decomposition, which might be a limitation if the data exhibits varying complexities across different dimensions.
3. **Overfitting and Underfitting**:
   * **Tucker Decomposition**: With its more detailed modeling, Tucker decomposition can better fit the training data without overfitting as easily as CP decomposition might.
   * **CP Decomposition**: Due to its simpler nature, CP decomposition might underfit the data if the chosen rank is too low, or overfit if the rank is too high without capturing the true underlying structure.
4. **Data Characteristics**:
   * The performance of tensor decompositions also depends on the characteristics of the data. Tucker decomposition may better capture the nuances and variations in the images, especially if the data has higher-order interactions that CP decomposition fails to model.