Project Plan

By: Tiffany Le

Project Description

Machine learning is widely adopted but often requires substantial computational resources. This research addresses the need for more efficient and accurate models by exploring various tensor fusion methods to increase predictive accuracy and reduce computational loads. Additionally, the proposed model integrates multi-modal inputs, combining visual imagery, patient demographics, and time-series data to perform a classification task. I aim to improve the model's accuracy by mapping each data modality to create a third-order tensor. A third-order tensor rather than concatenation allows the model to learn joint relationships between the different modalities, increasing accuracy. The model also employs a novel regularization method to reduce the impact of missing or corrupted data, allowing a more compact tensor decomposition—increasing model accuracy and computational load. Experimental results indicate a significant reduction in model parameters and inference time, demonstrating the potential of joint relationships from various modalities in real-time clinical applications.

Project Steps

1. **Problem Definition & Background Research**
    a. Define the classification or prediction task.
    b. Understand and define the dataset specifics/features.
    c. Review related literature on tensor fusion and multimodal learning techniques.
    d. Identify baseline models for benchmark comparison.
2. **Data Collection & Pre-Processing**
    a. Gather multi-modal data (e.g., time series, imagery, and structured data).
    b. Perform data cleaning and handle missing/unusable data.
    c. Standardize data for each modality.
3. **Feature Extraction & Tensor Fusion**
    a. Complete feature extraction on each modality to receive feature embeddings.
    b. Illustrate how each embedding will be mapped to form a third-order tensor.
    c. Implement tensor fusion to receive joint relationships and features.
    d. Compare fusion against simple concatenation models.
4. **Model Development & Regularization**
    a. Build the classification/prediction model.
    b. Introduce novel regularization such as Ridge or Lasso for better generalization.
5. **Training & Evaluation Against Other Methods**
    a. Train the model on the fused tensor.
    b. Evaluate performance using accuracy and inference time.
    c. Compare against the mentioned benchmark models.
6. **Experimental Analysis & Results**
    a. Analyze the impact of joint relationships on predictive/classification accuracy.

7. **Final Deliverables & Presentation**
    a. Summarize findings and methodologies in a research paper.
    b. Prepare a presentation and video recording highlighting the methodology and improvements in accuracy.
    c. Provide code/documentation for reproducibility.

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Dataset

To evaluate the effectiveness of our proposed approach, I will conduct experiments using the Alzheimer's Disease Neuroimaging Initiative v1.0 (ADNI1) dataset, specifically the medical imagery, time-series, and demographics datasets.

Proposed Deliverables

Part B Deliverables

- [ ] Literature Review & Problem Definition
- [ ] Initial Data Preprocessing & Cleaning
- [ ] Tensor Mapping & Fusion Strategy Proposal
- [ ] Baseline Model Implementation
- [ ] Preliminary Results Comparing Fusion vs. Concatenation
- [ ] Draft Report on Initial Findings

Part C Deliverables

- [ ] Optimized Model with Regularization
- [ ] Final Model Training & Evaluation Metrics
- [ ] Comparison with Benchmarks (Accuracy, Inference Time, Model Size)
- [ ] Experimental Analysis and Performance Discussion
- [ ] Complete Research Paper or Technical Report
- [ ] Final Presentation/Video with Key Findings
- [ ] Code & Documentation for Reproducibility