Multimodal Multihop Source Retrieval for WebQA

Nikhil Yadala[1], Paritosh Mittal[2], Saloni Mittal[1], Shubham Gupta[2]
[1]Language Technologies Institute, [2]Robotics Institute

Group 10

Introduction

- Information can be scattered across multiple sources; the proposed system should be capable of identifying and collating information critical to answering a question
- We aim to develop a system capable of selecting 'relevant' multimodal sources that can be combined to generate natural language answers to questions

Motivation and Challenges

Motivation

- Information is rarely localized within individual sources
- Information can come from any combination of modalities
- Modality agnostic approach to generalize and scale with web data

Challenges

- Significant data imbalance between positive and negative sources
- Need for collective reasoning and 'smart' information aggregation

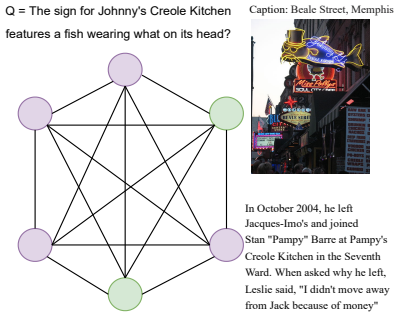
Baselines

- **Lexical Overlap:** A trivial baseline that outputs the top 2 sources with the highest lexical overlap between question and caption
- **VLP:** A transformer-based model trained on MLM and VQA is used for source retrieval
  - ► Processes each source independently and hence poor in capturing multihop aspect of selection
  - ► Resource intensive and difficult to train

Approach A: Dense Super-Node Graph

Intuition

- Unlike VLP, graphs can perform multihop reasoning on multiple sources
- It can learn meaningful connections between sources



Message Passing

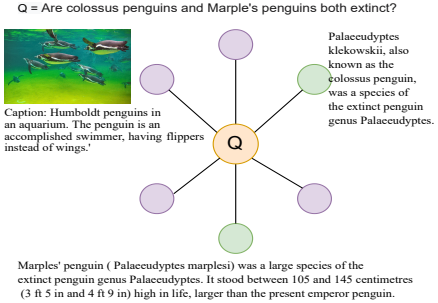
- Super node contains all information about source and question
- All nodes pertaining to a question are connected together (dense)
- Source selection is reduced to node classification (+/-)
- Message passing mathematical formulation

$$x_i' = W_1 x_i + W_2 \cdot mean_{j \in \mathcal{N}(i)} x_j$$

Approach B: Star Graph

Intuition

- Dense graph has a large number of uninformative connections (90% negative sources)
- Dropping irrelevant connections can improve learning



- All sources for a question are connected to a central question node
- We use multiple layers of the GNNs to enable message passing through the question node
- Sparse graph leads to faster training and convergence

Primitive Representations

Sentence embeddings from BERT to represent textual modality and ResNet-152 features to represent image modality while SOTA uses VinVL, X101fpn and VLP based feature representations

Results

Qualitative Results

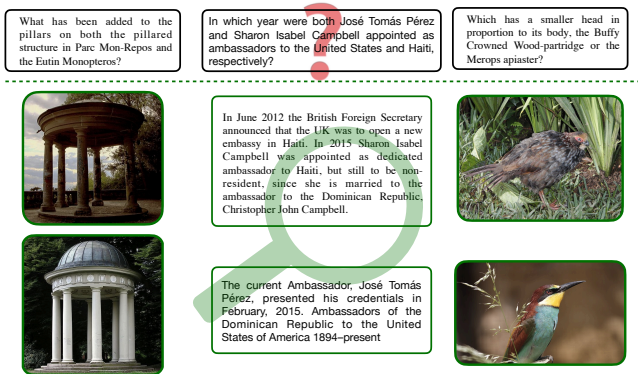


Figure 1:Queries along with Retrieved Sources from Star Graph

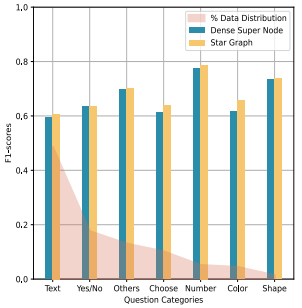
Quantitative Results

Modality	Lexical Overlap	VLP-VinVL	Super Node †	Star Graph †
Image	44.83	68.13	65.59	66.58
Text	33.78	69.48	59.39	60.74

Table 1:F1-score comparison of baselines with our methods. † Ours

Insights

- Even with 'primitive' representations, graph based approach has comparable performance to SOTA due to inherent 'multihop' reasoning ability
- Intuition-based sparse connections are faster and improve the performance



Ongoing Work

- Edge classification using graph attention networks
- Experiment with gated graphs for better information flow
- Using richer VinVL/CLIP features as node inputs