Multimodal Lecture Presentations Dataset: Understanding Multimodality in Educational Slides

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https://github.com/dondongwon/MLPDataset

Abstract
Lecture slide presentations, a sequence of pages that contain text and figures accompanied by speech, are constructed and presented carefully in order to optimally transfer knowledge to students. Previous studies in multimedia and psychology attribute the effectiveness of lecture presentations to their multimodal nature. As a step toward developing AI to aid in student learning as intelligent teacher assistants, we introduce the Multimodal Lecture Presentations dataset as a large-scale benchmark testing the capabilities of machine learning models in multimodal understanding of educational content. Our dataset contains aligned slides and spoken language, for 180+ hours of video and 9000+ slides, with 10 lecturers from various subjects (e.g., computer science, dentistry, biology). We introduce two research tasks which are designed as stepping stones towards AI agents that can explain (automatically captioning a lecture presentation) and illustrate (synthesizing visual figures to accompany spoken explanations) educational content. We provide manual annotations to help implement these two research tasks and evaluate state-of-the-art models on them. Comparing baselines and human student performances, we find that current models struggle in (1) weak crossmodal alignment between slides and spoken text, (2) learning novel visual mediums, (3) technical language, and (4) long-range sequences. Towards addressing this issue, we also introduce PolyViLT, a multimodal transformer trained with a multi-instance learning loss that is more effective than current approaches. We conclude by shedding light on the challenges and opportunities in multimodal understanding of educational presentations.

1 Introduction
Students today commonly learn through multimedia, including online lecture presentation recordings, educational mobile applications, and other digital resources [23]. In particular, slide-assisted instruction through lectures has become predominant in educational settings [30, 33, 34] and is widely considered by teachers and students as the preferred instructional tool [33, 37]. The effectiveness of lecture slides is supported by research in multimedia principles, which show that individuals learn more effectively from spoken (or written) language when accompanied by graphics rather than language in isolation [2, 24–26, 29]. The prevalence and effectiveness of lecture slides as an educational medium calls for AI systems that are also able to understand and communicate multimodal knowledge, in order to move closer towards intelligent teaching assistants [16]. More specifically, AI systems that can understand lecture slides could yield many exciting applications, such as an intelligent tutoring system that retrieves a slide to answer a student’s question, a recommender system that automatically generates a slide on-the-fly as the speaker is speaking, or an evaluation system that evaluates the quality of lecture presentations.

As a step towards this direction, we design the Multimodal Lecture Presentations Dataset (MLP Dataset) as a large-scale benchmark evaluating AI technologies in multimodal understanding of educational content. MLP Dataset contains over 9000 slides with natural images, diagrams, equations, tables and written text, aligned with the speaker’s spoken language. These lecture slides are sourced

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from over 180 hours worth of educational videos in various disciplines such as anatomy, biology, psychology, speaking, dentistry, and machine learning. To benchmark the understanding of multimodal information in lecture slides, we introduce two research tasks which are designed to be a first step towards developing AI that can explain and illustrate lecture slides: automatic retrieval of (1) spoken explanations for an educational figure (Figure-to-Text) and (2) illustrations to accompany a spoken explanation (Text-to-Figure)\(^1\). To enable these tasks, we manually annotated the slide segments to accurately capture alignment between spoken language, slides, and figures (diagrams, natural images, table, equations).

MLP Dataset and its tasks bring new research opportunities through the following technical challenges: (1) addressing weak crossmodal alignment between figures and spoken language (a figure on the slide is often related to only a portion of spoken language), (2) representing novel visual mediums of man-made figures (e.g., diagrams, tables, and equations), (3) understanding technical language, and (4) capturing interactions in long-range sequences. Through human and quantitative studies, we find that current multimodal models struggle with the aforementioned challenges. We work towards addressing weak alignment and novel visual mediums by introducing PolyViLT, a multimodal transformer trained with a multi-instance learning loss. Although PolyViLT presents some improvement, MLP Dataset still offers novel challenges that will spark future research in educational content modeling, multimodal reasoning, and question answering.

2 Related Work

The effectiveness of lecture slides as a medium of transferring information can be explained by five multimedia learning principles [15]. Firstly, the multiple representation principle states that individuals learn more effectively from graphics accompanied by spoken or written verbal information than solely spoken language. This principle is supported by dual-route processing mechanisms of working memory and comprehension processes, where integration of verbal and nonverbal information benefits formation of representations in working memory. [25] [24] [29] [2] [26]. Secondly, the contiguity principle expounds on reducing the spatio-temporal separation between different forms of information, which decreases the amount of effort required to build a coherent mental representation [4] [28]. Third, redundancy, the exposure to complementary but identical information in different modalities, improves learner’s working memory (auditory, visual). Fourth, coherence: restricting the information presented to only essential information allows the learner to integrate key concepts and relationships [17]. Finally, signalling provides learner information regarding the overall hierarchical structure of the presentation [25].

\(^1\)Text-to-Figure can be thought as a recommender system assisting a lecturer by providing recommendations of figures when building presentation slides according to the lecturer’s planned transcript. On the other hand,
Table 1: Comparison with existing lecture-based datasets, (A) represents automatic processing, (M) represents manual processing. MLP Dataset is the first of its kind to offer slide segmentation, aligned spoken language, slide text, and visual figures, while being publicly available.

|                | Slide Segments | Slide Figures | Slide Text | Spoken Language | # Videos | # Hours | # Slides |
|----------------|----------------|---------------|------------|-----------------|-----------|---------|----------|
| VLEngagement   | ✓             | ✓             | ✓          | ✓               | 11568     | ✔       | ✔        |
| LectureBank    |✓ (M)         | ✓             | ✓          | ✓               | 1352      | ✔       | ✔        |
| ALV            | ✓             | ✓             | ✓          | ✓               | 1498      | ✔       | ✔        |
| LectureVideoDB | ✓ (M)       | ✓             | ✓          | ✓               | 24        | ✔       | ✔        |
| GoogleI/O      | ✓             | ✓             | ✓          | ✓               | 209       | 2350    | ✔        |
| LaRochelle     | ✓             | ✓             | ✓          | ✓               | 47        | ✔       | ✔        |
| MLP Dataset    | ✓ (M)        | ✓             | ✓          | ✓               | 334       | 9031    | ✔        |

Given the effectiveness of lecture slides as a medium of presenting information, future AI should be able to learn and extract from the carefully curated, rich information in lecture slides. Recent work towards computational modeling of lecture slides include LectureBank [12, 22], ALV [14], VLEngagement [3], LectureVideoDB [11], GoogleI/O [5], and LaRochelle [38]. We summarize and compare these datasets with our proposed MLP Dataset in Table 1. We also highly recommend readers to refer to Appendix A where we present detailed descriptions and differences of previous datasets. To the best of our knowledge, MLP Dataset is the first of its kind to offer slide segmentation, aligned spoken language, slide text, and visual figures, while being publicly available for the research community.

3 Multimodal Lecture Presentations Dataset

The Multimodal Lecture Presentations Dataset is designed as a benchmark to develop AI models capable of understanding multimodal information present in lecture slides. Our dataset offers segmented slides, their aligned spoken language and visual elements (figures, diagrams, natural images, tables), and OCR text output for slide text.

3.1 Problem Definition

In order to benchmark an AI technology’s understanding of multimodal education content and move closer to automatic generation of captions and figures, we measure its ability to associate a visual figure with a spoken explanation. We define figures as a visual illustration consisting of text, images, drawings (i.e., diagrams, images, equations, or tables). We design 2 proxy tasks, where (1) visual figures are retrieved given spoken language (Text-to-Figure) and (2) spoken explanations are retrieved from visual figures (Text-to-Figure). In contrast to many prior crossmodal retrieval setups which assume one-to-one mappings between modalities [39], lecture presentations are unique in the presence of weak crossmodal alignment between spoken language and figures. There could exist $n > 1$ visual figures for a single spoken speech segment $s$ and a figure could be aligned partially to the spoken segment (i.e., a part of the spoken segment is used to explain the figure). Thus, a core challenge lies in addressing weak crossmodal alignment. Formally, let $D = (S, V)$ be our dataset consisting of spoken language $S$ and figures $V$. The goal is to learn an embedding space that can quantify the similarity between the figure and spoken language. As a result, given a segment of spoken language $s \in S$, one could retrieve the set of aligned visual figures $\{v_k, v_{k+1}, ..., v_{k+n}\} \subseteq V$.

3.2 Dataset Statistics

Our MLP Dataset consists of 9031 slides, 8598 figures, 28000 unique words, 1.6 million total words from 334 educational presentation videos with a total duration of 187 hours. As shown in Table 2(b) Per slide, there are 185.83 words spoken on average and 135 words in median. Each slide’s duration is an average of 72.6 seconds or a median of 54.9 seconds as shown in Figure 2(e). Among the 8598 figures, 3877 (45.1%) are natural images, 4018 (46.7%) are diagrams, 301 (3.5%) are tables, 402 (4.6%) are equations, shown in Table 2(d). Each slide has a median of 1 (or 0.94 on average) figure, shown in Table 2(c), a median of 26 written words (or 28.95 on average), displayed in Table 2(a). Furthermore, when available, we provide the mouse traces which hover over the region the speaker is describing. There are 12.52 seconds of mouse trace data per slide on average and 4.6 in median, as shown in Table 2(f).

Figure-to-Text can be used by an intelligent tutoring system to retrieve relevant explanations to help a student when given a query of a visual diagram.
dentistry, speaking, machine learning taught by 10 speakers. The distribution of the number of slides per speaker is shown in Table 2(g).

### 3.3 Data Collection and Preprocessing

The Multimodal Lecture Presentations Dataset is developed from a curated list of lecture presentation videos, which are downloaded from YouTube. Spoken language is then extracted from speech via automatic speech recognition. We manually annotate for the slide segments as well as figure bounding boxes and corresponding labels in order to perform retrieval tasks between slide-level segments spoken text and individual visual figures. In addition, in order to utilize the language information in figures, the texts in the slide are automatically extracted via OCR. A visual outline the data collection and processing steps taken to create MLP Dataset is shown in Figure 3.

#### Video Acquisition

413 English educational videos were downloaded from YouTube. From the initial list, we filtered and curated a smaller list of 10 speakers according to the following criteria: (1) the material must be presented in a slide-based style, (2) the slides must be stationary (i.e. external video clips cannot be played), and (3) the speaker makes use of their mouse to refer to specific figures on the slide. After filtering, 334 videos remained.

#### Slide Segmentation

The quality of segmentation is crucial to our task of retrieval, therefore, we collected manual human annotations on MTurk. We presented the annotator with a lecture video and asked the annotator to use a slider to navigate to the end of each slide and mark its precise timestamp. A screenshot of this experiment can be found in Appendix C.

In order for ensure the high quality of segmentations, we conduct the annotation process in multiple steps. (1) An internal team manually annotated 10 lecture videos for groundtruth annotations. (2) The experiment was made available to 100 MTurkers. (3) We evaluate their results, marking an annotation as correct if theirs matched ours within a 1 second interval. (4) Annotators who were able to perform above a 90% correctness threshold were assigned the full set.

#### Figure Annotation and Labeling

Our dataset is unique from previous datasets as our focus is centered around figure-level retrieval. In order to enable this task, our data must consist of precise bounding boxes and labels for each figure. Therefore, we design an MTurk experiment where annotators are shown slides and asked to create a bounding box around figure instances and label their classes. Our class labels are inspired from PRImA[1], a dataset that consists of layouts from
a) **Video Acquisition (Manual):** Acquired educational lecture videos from Youtube across a range of speakers and subjects (psychology, computer science, biology, etc.) in a presentation-style.

b) **Slide Segmentation (Manual):** MTurk annotators annotated distinct slide segments within an educational lecture video by marking the timestamp before each new slide transition.

c) **Figure Annotations (Manual):** Annotators were asked to draw bounding boxes over figures, formulas, tables, and natural images. We provided additional instructions to exclude speakers/logos.

d) **OCR (Automated):** We used PyTesseract to extract OCR output corresponding to the text on each slide segment.

e) **ASR Alignment (Automated):** We used Google ASR Video-Model to extract the text alignment from speech for each slide segment.

f) **Trace Extraction (Automated):** We calculate the difference between frames to extract moving traces.

![Figure 3: Overview of our data collection and preprocessing steps with a summary of each step. Best viewed zoomed in and in color.](image)

To obtain precise and accurate figure annotations, we follow a multi-phase process. (1) An internal team manually annotated 10 lecture videos for groundtruth figure annotations and labels. (2) We make the experiment available to 100 MTurkers for 10 different slides. (3) We manually evaluate the annotations, marking an annotation as correct if the annotators had the same number of figures, equivalent types, and high overlap of bounding boxes. (4) Annotators who were able to perform above a 90% correctness threshold were assigned the full set. (5) To ensure the absolute highest quality of figure annotations, our internal team of annotators manually corrected all the annotations for any mislabeled bounding box annotations or incorrect regions.

**Text Extraction: ASR & OCR:** We use Google ASR to extract spoken language from audio. We use the Video-Model, which has a reported WER of 16% (Amazon: 22%, Microsoft 24%, IBM Watson 29%, Google Speech-Model 37%). We manually verify 100 random segments in the dataset, and find that the WER is 17.1%. To extract OCR text from the images of slides, we use Tesseract. We manually verify 100 random slides in the dataset, and find that the WER is 37.82%.

**Mouse Trace Location Extraction:** We extract the mouse trace location to be used as an additional grounding signal between visual objects and language. For each segmented slide, the background is static and the only object that is moving is the pointer. If there is any movement, we consider that as the pointer location. We manually verify 100 random mouse trace location in the dataset, and find that the percentage of correct keypoints (PCK) with a threshold of 50 pixels, is 77.1%.

## 4 Experimental Setup

The MLP Dataset is designed to examine multimodal model’s understanding of educational material, as measured by its performance on text-to-figure and figure-to-text retrieval. We evaluate multiple state-of-art model’s performance in comparison with human student performance. We are interested in understanding how current state-of-the-art models perform on different figure types (diagrams, images, equations, tables), long range sequences, and technical language. We also introduce PolyViLT, a multi-instance learning multimodal transformer that utilizes both vision and language information in slide figures.
4.1 Baselines

We select previous baselines PVSE \cite{36} and PCME \cite{7} that are designed for cross-modal retrieval particularly in scenarios with weak alignment. We also measure CLIP \cite{32} performance, as its zero-shot image-text matching performance is well recognized in the community.

CLIP \cite{32} is an established baseline for image-text matching. We use a pre-trained CLIP model to embed pairs of figures and text and rank according to their similarity scores for retrieval.

PVSE \cite{36} is designed to model one-to-many alignment for cross-modal retrieval, by encoding visual and text features as $K$ possible embeddings and training with a multiple instance loss that rewards weak cross-modal alignment (i.e., the best pair among $K^2$ pairs is rewarded).

PCME \cite{7} handles pairwise semantic similarities and uncertainty in cross-modal retrieval. It models each modality as probabilistic distributions in a common embedding space using Hedged Instance Embeddings (HIB) \cite{27} and utilizes a soft version of the contrastive loss to handle weak alignment.

4.2 PolyViLT: A Proposed Model for Weak Image-Text Alignment

On top of these baselines, we further introduce Polysemous-ViLT (or PolyViLT), which is designed to handle vision and language inputs (e.g., diagrams) and weak cross-modal alignment. Previous approaches were designed specifically for the task of cross-modal retrieval on datasets consisting of only natural images and text. However, to perform well on retrieval problems involving figures, models must utilize text information present in the figure, as they could provide valuable signals to the model. Our approach utilizes local feature transformers in PVSE \cite{36}, a multi-instance learning loss \cite{9} and a ViLT figure encoder \cite{19} to utilize both vision and language information in figures. We refer the readers to Figure 5 for details and figure of the model architecture.

ViLT Figure Encoder

We utilize the ViLT model \cite{19} as a backbone encoder to contextualize the text and vision information present in figure. Given an image of a figure, the accompanying text (from OCR output) on the figure is tokenized with BERT \cite{8}, patches of the diagram image is flattened and linearly projected, and fed in as a sequence to a transformer encoder. We initialize the ViLT encoder with pretrained weights trained on masked language modelling and image-text matching before training on our dataset.

Multiple Instance Learning (MIL)

To account for the partial alignment between figures and spoken language, we represent the spoken language with $K$ embeddings, capturing different words of the speech, inspired by local feature transformers in \cite{36}. The local $K$ embedding are combined with global information via residual connections. Then, we utilize the MIL objective \cite{9}, which assume that there is a partial match between a figure and $K$ local embeddings of the spoken language.

4.3 Human Student Performance

To measure human student performance, we randomly sampled 10 figures from the unseen test set for each speaker from 3 random seeds. For Figure-to-Text, a student is shown one figure image, all the spoken language aligned to the 10 figures in the sample and is asked to select the most relevant spoken language. For Text-to-Figure, the annotator is shown one spoken language, all the figure and
Figure 5: Overview of the key components of our proposed PolyViLT model. The diagram’s text and image patches are input into a ViLT-based transformer encoder, and the spoken language BERT embedding is transformed into $K$ representations. A MIL Loss [9] is used to address weak crossmodal alignment and find partially aligned instances.

is asked to select the most relevant figure. We report recall@1 metric for this sample for all of our baseline models for fair comparison.

5 Results
5.1 Model and Human Performance
The performance of all models can be seen in Table 2. PolyViLT outperforms previous state-of-the-art approaches in both Figure-to-Text retrieval and Text-to-Figure Retrieval. The second best performing model is PVSE [36], which further justifies our reasoning behind utilizing local feature transformers and the MIL loss. Surprisingly, CLIP’s zero-shot performance often is worse than Random, which indicates that large-scale pre-training on natural image-text pairs may not be sufficient for our task. The detailed results for each speaker can be found in Appendix F. We also provide human student retrieval performance in Figure 4. We see that all methods fall well below human students’ performance, even PolyViLT, the closest method, is 47.68% worse for Text-to-Figure retrieval and 43.63% worse for Figure-to-Text retrieval, which demonstrates the challenging nature of our dataset.

In the following sections, we perform error analysis to uncover the concrete challenges presented in MLP Dataset.

5.2 Performance on Novel Visual Mediums
We first investigate the impact of novel visual mediums such as man-made figures (e.g., diagrams, tables, and equations) on model performance. We report recall@10 scores conditioned on each type in Table 3, and find that PolyViLT outperforms other baselines for most figure types. Interestingly, we can see that for natural images, previous approaches perform worse than PolyViLT. Whereas we believed that PolyViLT’s main advantage is in its use of text information, it outperforms previous approaches even when no text information is used. This indicates that the usage of a ViT encoder [10] is superior over using local and global feature transformers as proposed in PVSE [36] and PCME [7] even for natural images. We also find models struggle particularly on equations. As mentioned in Section 4.2 this could be attributed to the significant domain difference between the pretraining domain (natural images, non-educational language) of ViLT [19] and equations. PVSE [36] is initialized with random weights, therefore is unaffected.

5.3 Technical Language and Long Range Sequences
The second challenge we investigate is the presence of technical language beyond commonly spoken and written text. Table 4(b) shows the number of subwords tokenized by HuggingFace’s BERT Tokenizer [8][40], which represents the number of Out-of-Vocabulary (OOV) tokens, a proxy measure for how much external knowledge is required to understand technical language. With an increasing...
Models Figure-to-Text Text-to-Figure

| Models          | Recall@1   | Recall@5   | Recall@10  | Recall@1   | Recall@5   | Recall@10  |
|-----------------|------------|------------|------------|------------|------------|------------|
| Random          | 1.36 ± 0.22| 7.63 ± 0.88| 15.81 ± 0.7| 2.15 ± 0.61| 8.64 ± 1.1 | 16.38 ± 1.91|
| CLIP [32]       | 2.05 ± 0.7 | 7.4 ± 0.15  | 17.65 ± 1.02| 1.58 ± 0.56| 6.89 ± 1.18| 13.78 ± 0.55 |
| PVSE [36]       | 3.17 ± 0.68| 12.44 ± 1.28| 22.01 ± 0.61| 2.81 ± 0.27| 11.87 ± 1.24| 21.2 ± 0.63 |
| PVSE (BERT) [36, 8] | 2.96 ± 0.76 | 10.96 ± 0.52 | 18.54 ± 0.99 | 2.43 ± 0.05 | 11.21 ± 1.11 | 18.51 ± 1.1 |
| PCME [7]        | 2.31 ± 0.41| 8.83 ± 0.34 | 16.43 ± 0.67| 2.12 ± 0.36| 8.68 ± 0.14 | 16.9 ± 1.1  |
| PCME (BERT) [7, 8] | 1.93 ± 0.26 | 8.27 ± 0.95  | 15.76 ± 1.64| 1.93 ± 0.26| 8.36 ± 1.08 | 15.85 ± 1.77 |
| PolyViLT + Trace| 3.85 ± 0.91| 17.77 ± 1.88| 28.26 ± 1.78| 5.38 ± 0.78| 19.66 ± 2.39| 32.26 ± 0.59 |
| PolyViLT        | 4.94 ± 0.55| 19.16 ± 0.69| 30.35 ± 0.55| 6.14 ± 1.25| 23.19 ± 0.68| 33.22 ± 1.73 |

Table 2: Comparison between PolyViLT vs previous state-of-the-art models for crossmodal retrieval with multiple instance learning across all dataset for 3 random seeds, standard deviation bars are reported. PolyViLT outperforms all previous state-of-the-art approaches by a large margin.

Models Figure-to-Text: Recall@10 Text-to-Figure: Recall@10

| Models          | Diagram | Image | Table | Equation | Diagram | Image | Table | Equation |
|-----------------|---------|-------|-------|----------|---------|-------|-------|----------|
| CLIP [32]       | 6.2 ± 0.57| 5.77 ± 0.73| 6.2 ± 0.43| 2.83 ± 1.11| 6.5 ± 1.27| 6.0 ± 0.22| 6.9 ± 2.5 | 3.5 ± 0.96 |
| PVSE [36]       | 8.2 ± 0.93| 9.6 ± 0.57| 7.27 ± 0.29| 12.27 ± 3.27| 7.6 ± 1.3 | 10.33 ± 1.76| 6.97 ± 4.15 | 4.47 ± 4.66 |
| PCME [7]        | 6.0 ± 0.37| 6.9 ± 0.22| 6.3 ± 3.28| 2.93 ± 3.27| 5.9 ± 0.49| 6.87 ± 0.26| 6.3 ± 3.38 | 2.93 ± 3.27 |
| PolyViLT        | 18.53 ± 1.65| 15.2 ± 0.91| 15.83 ± 2.67| 5.33 ± 5.37| 18.53 ± 1.89| 20.13 ± 0.7 | 19.17 ± 6.34 | 9.97 ± 3.48 |

Table 3: Comparison of recall@10 scores for baselines conditioned on types of figures, mean and standard deviations are reported for 3 seeds across all speakers. PolyViLT outperforms previous baselines in most cases, except for equation text-to-figure retrieval.

number of subwords, there is a drop in performance, indicating that our models struggle to quickly acquire technical information or require external knowledge to perform well.

Furthermore, our dataset poses challenges in capturing information in long range language sequences due to its educational nature. In Table 3, we report recall@10 scores conditioned on the number of spoken words. PolyViLT’s performance peaks between 100 and 200 words, and decreases with increasingly longer spoken phrases, or very short spoken phrases (under 100). This calls for a need to develop models for extremely long-range and short-range sequences. We refer the readers to Appendix D where we display examples of instances where our current baselines fail when technical knowledge or understanding of long range interactions are required, and Appendix E for the negative impacts of long range sequences and technical language on other baseline models.

5.4 Importance of MIL objective

5.5 Using Mouse Trace as a Grounding Signal

Finally, we experiment with utilizing mouse trace as an additional grounding signal to capture crossmodal alignment. With this intuition, we represent mouse traces as a one-hot vector with length equivalent to the spoken language sequence. For the indices corresponding to words when the mouse hovered over the figure, we assign it the value 1, indicating that the spoken word is directly aligned to the given figure and is conceptually similar to hard attention. We re-parameterize this categorical distribution with a Gumbel-Softmax [18], and use a dot-product attention with skip connections to fuse spoken language and mouse traces. The result for this model is shown in Table 2 as ‘PolyViLT + Trace’. For certain speakers, the inclusion of mouse-trace data offers better performance. We refer the readers to Appendix F for speaker-specific studies. Future work should aim at better utilizing the valuable information in mouse traces as a grounding signal [21, 31].

6 Discussion

Limitations: Although our dataset presents exciting opportunities, it comes with its limitations. There exists an imbalance in slide distribution amongst speakers. In Figure 2 we show that the dental topic encompasses 28.66% of slides whereas psychology encompasses a much smaller portion of 1.53% of
Table 4: (a) PolyViLT performance drops for very short or very long sequences, (b) or with increasing number of subwords (technical terms).

| PolyViLT r@10 | (a) Length of Spoken Language | (b) Number of Subwords |
|---------------|-------------------------------|------------------------|
|               | <100 | 100 - 200 | 200 - 400 | 400 - 600 | 600+ | <10 | 10 - 20 | 20-30 | 30 - 50 |
| Figure-to-Text | 0.195 | 0.0276 | 0.0186 | 0.0227 | 0.0175 | **0.218** | 0.0191 | 0.0128 | 0.0132 |
| Text-to-Figure | 0.177 | 0.0280 | 0.0207 | 0.0186 | 0.014 | **0.191** | 0.0156 | 0.0136 | 0.0124 |

Table 5: Using MIL to handle weak crossmodal alignment leads to performance boosts.

| Figure-to-Text | Text-to-Figure |
|----------------|----------------|
| bio-1 | dental | ml-1 | bio-1 | dental | ml-1 |
| No MIL | 26.18 ± 3.92 | 12.15 ± 1.67 | 12.58 ± 4.62 | 28.74 ± 1.32 | 12.32 ± 1.37 | 22.23 ± 3.83 |
| MIL | **31.29 ± 7.51** | **17.07 ± 1.66** | **19.32 ± 3.04** | **32.24 ± 5.25** | **20.23 ± 0.12** | **24.84 ± 8.93** |

slides. In addition, most topics fall under science and math, leaving humanities unrepresented in this dataset. Similarly, quantitative figures may not be adequately represented as tables and equations represented only 8.2% of the dataset. Further studies on using mouse traces as input signals must be done. Speakers may not consistently use mouse traces, leading to some slides with stronger alignment and some slides with weaker alignment. Finally, this dataset does not encompass other miscellaneous information a speaker might present during their lecture such as animations, speech tone, or extraneous information presented through the form of videos, websites, virtual whiteboards, or other redirected sites.

Broader impacts: There may be downstream effects in training models exclusively on this dataset, since content in humanities may not be equally represented. Social biases could also be encoded into the dataset based on the choice of images and content that speakers decide to include in their lectures, such as images with predominantly male representation or primarily English language. We believe that MLP Dataset is a first step towards tackling multimodality and alignment in educational slides, and we aim to further expand it with diversity in speakers, languages, subjects, and lecture styles.

7 Conclusion

In conclusion, we present the Multimodal Lecture Presentations Dataset as benchmark for developing AI technologies that can communicate multimodal knowledge in educational content. Our diversely sourced and richly annotated dataset contributes two challenging research tasks as a step towards educationally relevant goals: (1) automatic retrieval of spoken explanations given figures and (2) automatic retrieval of illustrative figures given spoken explanations. Through benchmarking existing and newly proposed models, we outline future research directions in tackling weak crossmodal alignment, novel visual mediums, technical language, and long-range sequences to bring us closer towards intelligent and accessible tutoring aids.
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A Descriptions of Previous Lecture Datasets

LectureBank Dataset [22] is a manually-collected dataset of lecture slides, consisting of 1352 online lecture pdf files from 60 courses in Computer Science in 5 sub-domains: Machine Learning, NLP, DL, and IR. The dataset is annotated for each lecture’s topic and prerequisite relation topics based on taxonomy from [12]. This data, does not contain aligned transcripts and was used to predict prerequisite relations for a given lecture slide.

ALV [14] is a lecture video dataset of artificially-generated lectures, where transcripts from lectures are randomly split in fragments then assembled by combining (stitching) exactly 20 randomly selected fragments from various videos. The resulting dataset only consists of transcripts. This work was developed for the purpose of evaluating lecture video fragmentation techniques.

VLEngagement [3], is dataset which was designed to study engagement in video lectures, where content-based (stop-word counts) and video-specific features (silence, video duration) are extracted from publicly available scientific video lectures

LectureVideoDB [11] is a dataset consisting of 5000 frames of lecture videos, with annotated text characters developed for the purpose of text detection and recognition in Lecture Videos.

GoogleI/O [5] is a dataset consisting of 209 presentation videos from the Google I/O conferences in the years 2010-2012. In this dataset, the authors offer only textual information from the speech and the slides. The retrieval task is done at the video level, where entire transcripts are matched with all the text in a presentation.

LaRochelle [38] 47 French lecture recordings from author’s lab, Similar to [5], the authors study video-level retrieval. In addition, the authors experiment with cross-modal retrieval where a bag of words approach is used for the text and visual tokens.

B MTurk: Annotators

For each task, we approximate the time each takes with internal annotators to ensure a minimum payment of $8 per hour. For the task of slide segmentation, as annotators are simply required to scroll through the video to find transition points, we pay 50 cents for a 15 minute long video (i.e $2 for an hour long video). We pay annotators a total amount of $856.95 for this task. For the task of figure annotations, we pay the annotators 5 cents per slide, where annotators are expected to spend around 20 seconds per slide. As a result, we spent $451.55 for a total of 9031 slides.
C  MTurk: Slide Segmentation

Figure 6: MTurk Screenshot and Instructions for Slide Segmentation

The diversity of large animals increased dramatically during the “Cambrian explosion”

- The Cambrian explosion (535 to 525 million years ago) marks the earliest fossil appearance of many major groups of living animals.

Instructions

Find exact transition points between slides in the lecture video.

Important: Do NOT watch the entire video! Instead, use the slider on the video to find the transitions, for more details check out the Examples Tab.

When you find the transition point, stop the video and click on Annotate.

Your annotations will show up on the right side of the video. If you think you have made a mistake, you can edit the start time or the type of phase by clicking Edit next to the annotation.

You can also go back to the exact point in your annotations by clicking Go Here next to the annotation.

Important: Lastly, after annotating all the transitions, click on Submit to complete the HIT. We will be judging (and eventually approving the HIT) the quality of the annotations based on the accuracy of the annotations.
D MTurk: Figure Annotation

Figure 7: MTurk Screenshot and Instructions for Figure Annotations

Annotation Instructions

1. To draw a bounding box click the correct label, and draw a rectangle around the requested term.
2. If the target goes off the screen, label up to the edge of the image.
3. Capture each distinct image that is on the slide.
4. Do not mark logos or other images that do not add informative content to the topic of the slide.
5. Only capture slide images - do not mark speaker faces or videos stills that may have been played on a slide.
6. If there is nothing to label, mark the checkbox “Nothing to Label” next to the submit button.
7. You can delete an annotation by clicking the bounding box you just made and pressing delete on your keyboard.

Bounding Box Instructions

Use the bounding box tool to draw bounding boxes over the requested regions. If they appear on the slide:

Shown below are the definitions for each requested region:

1. Images: photographs of natural images, can contain text.

2. Diagram: man-made diagrams, figures, flow chart, can contain text.

3. Table: arrangement of information or data, typically in rows and columns, can contain text.

4. Equation: formulas or math equations, can contain text.

Figure 7: MTurk Screenshot and Instructions for Figure Annotations
E Training Details

We use PyTorch as the auto-differentiation library to train all our models. For each speaker, with split the data such that a random 80% is used as training data and the remaining 20% is used for test (the data is split according to each random seed). In our experiments, we use the following hyperparameters. We train for 100 epochs, and our batch size is 8.

We also utilize the 3 losses (MIL with a margin parameter $\lambda_m$, Diversity $\lambda_{div}$, Domain Discrepancy $\lambda_{dom}$) as motivated in [36], we refer the audience to the original paper for the formulation of these losses. We use the default parameters, $\lambda_m = 0.1, \lambda_{div} = 0.01, \lambda_{dom} = 0.01$. For the number of locally guided features $K$ as shown in Figure 5, we use $K = 5$. Further finetuning on these hyperparameters is a future direction of study to boost performance.

As mentioned in Section 4.2, we use a pre-trained backbone ViLT encoder from HuggingFace, by the original authors, which has been trained on masked language modelling and image-text matching (‘ViLT-b32-mlm-itm’) [40]. We will release the full code base with our default hyperparameters.

The models were trained with CMU Multicomp Lab’s internal cluster. The average model train runtime was around 8 hours on Titan X 1080 GPUs.
### F Comprehensive Results for Each Speaker

| Speaker | Recall@1 | Recall@5 | Recall@10 | Recall@1 | Recall@5 | Recall@10 |
|---------|----------|----------|-----------|----------|----------|----------|
| **Recall@1** | **Recall@5** | **Recall@10** | **Recall@1** | **Recall@5** | **Recall@10** |
| **Random** | 0.27 ± 0.38 | 3.18 ± 2.4 | 5.77 ± 1.73 | 0.26 ± 0.36 | 3.38 ± 1.42 | 8.07 ± 3.8 |
| **CLIP** | 0.53 ± 0.37 | 4.53 ± 1.21 | 9.11 ± 1.11 | 0.54 ± 0.38 | 3.19 ± 1.63 | 7.17 ± 3.15 |
| **PVSE** | 2.1 ± 0.4 | 7.33 ± 1.14 | 12.76 ± 2.07 | 1.83 ± 0.36 | 8.09 ± 0.92 | 11.73 ± 0.88 |
| **PVSE (BERT)** | 2.62 ± 0.43 | 5.49 ± 0.12 | 10.48 ± 1.71 | 1.04 ± 0.36 | 7.01 ± 2.21 | 10.68 ± 1.82 |
| **PCME** | 1.3 ± 0.71 | 4.18 ± 0.32 | 7.83 ± 0.16 | 1.3 ± 0.71 | 4.18 ± 0.32 | 7.83 ± 0.16 |
| **PCME (BERT)** | 1.3 ± 0.71 | 3.92 ± 0.63 | 8.09 ± 0.92 | 1.3 ± 0.71 | 3.92 ± 0.63 | 8.09 ± 0.92 |
| **Ours** | 11.23 ± 0.91 | **30.82 ± 6.1** | **42.31 ± 4.82** | **13.79 ± 2.34** | **34.34 ± 8.91** | **44.9 ± 6.53** |
| **Ours w/ Trace** | 9.64 ± 3.08 | **31.05 ± 6.71** | **46.49 ± 2.67** | 10.71 ± 0.54 | **36.86 ± 2.33** | **49.85 ± 1.14** |

| **Recall@1** | **Recall@5** | **Recall@10** | **Recall@1** | **Recall@5** | **Recall@10** |
| **Random** | 1.75 ± 2.48 | 21.05 ± 8.59 | 50.87 ± 9.92 | 8.77 ± 2.48 | 31.58 ± 8.6 | 56.14 ± 8.94 |
| **CLIP** | 7.12 ± 2.42 | 23.2 ± 6.48 | 57.21 ± 7.01 | 3.51 ± 4.96 | 16.08 ± 8.61 | 37.43 ± 3.61 |
| **PVSE** | 7.02 ± 2.48 | 38.6 ± 2.48 | 66.67 ± 2.48 | 7.02 ± 2.48 | 38.6 ± 5.65 | 68.42 ± 0.0 |
| **PVSE (BERT)** | 5.26 ± 4.3 | 33.33 ± 4.96 | 61.4 ± 8.94 | 5.26 ± 0.0 | 33.34 ± 6.56 | 52.63 ± 8.59 |
| **PCME** | 5.26 ± 0.0 | 28.07 ± 4.96 | 56.14 ± 2.48 | 5.26 ± 0.0 | 28.07 ± 4.96 | 56.14 ± 2.48 |
| **PCME (BERT)** | 5.26 ± 0.0 | 28.07 ± 2.48 | 52.63 ± 0.0 | 5.26 ± 0.0 | 28.07 ± 2.48 | 52.63 ± 0.0 |
| **Ours** | **7.02 ± 2.48** | **54.39 ± 6.56** | **78.95 ± 4.3** | **8.77 ± 2.48** | **57.89 ± 4.3** | **75.44 ± 6.56** |
| **Ours w/ Trace** | **8.77 ± 4.96** | **49.12 ± 6.56** | **73.68 ± 7.44** | 7.02 ± 6.56 | **49.12 ± 8.94** | **77.19 ± 6.56** |

| **Recall@1** | **Recall@5** | **Recall@10** | **Recall@1** | **Recall@5** | **Recall@10** |
| **Random** | 0.79 ± 0.43 | 3.13 ± 1.19 | 4.7 ± 0.89 | 8.77 ± 2.48 | 31.58 ± 8.6 | 56.14 ± 8.94 |
| **CLIP** | 0.51 ± 0.03 | 3.41 ± 1.53 | 5.7 ± 2.4 | 3.51 ± 4.96 | 16.08 ± 8.61 | 37.43 ± 3.61 |
| **PVSE** | 0.97 ± 0.07 | 4.05 ± 0.54 | 6.0 ± 1.06 | 7.02 ± 2.48 | 38.6 ± 5.65 | 68.42 ± 0.0 |
| **PVSE (BERT)** | 0.79 ± 0.43 | 5.07 ± 1.15 | 8.55 ± 1.52 | 5.26 ± 0.0 | 33.34 ± 6.56 | 52.63 ± 8.59 |
| **PCME** | 0.66 ± 0.29 | 2.11 ± 0.4 | 4.68 ± 0.49 | 5.26 ± 0.0 | 28.07 ± 4.96 | 56.14 ± 2.48 |
| **PCME (BERT)** | 0.48 ± 0.03 | 2.39 ± 0.23 | 4.68 ± 0.49 | 5.26 ± 0.0 | 28.07 ± 2.48 | 52.63 ± 0.0 |
| **Ours** | **4.23 ± 0.9** | **12.53 ± 2.6** | **19.15 ± 1.29** | **8.77 ± 2.48** | **57.89 ± 4.3** | **75.44 ± 6.56** |
| **Ours w/ Trace** | **2.91 ± 0.82** | **7.14 ± 1.08** | **12.65 ± 2.73** | 7.02 ± 6.56 | **49.12 ± 8.94** | **77.19 ± 6.56** |

| **Recall@1** | **Recall@5** | **Recall@10** | **Recall@1** | **Recall@5** | **Recall@10** |
| **Random** | 0.57 ± 0.4 | 3.68 ± 1.63 | 6.58 ± 1.56 | 1.16 ± 1.11 | 4.07 ± 1.72 | 8.35 ± 1.33 |
| **CLIP** | 0.0 ± 0.0 | 5.4 ± 1.52 | 11.35 ± 2.29 | 0.85 ± 0.02 | 3.66 ± 1.04 | 7.09 ± 1.22 |
| **PVSE** | 1.14 ± 0.81 | 6.61 ± 0.93 | 15.8 ± 1.33 | 1.16 ± 0.43 | 6.34 ± 1.25 | 12.35 ± 1.28 |
| **PVSE (BERT)** | 2.87 ± 1.11 | 7.47 ± 0.94 | 12.93 ± 1.45 | 1.43 ± 0.39 | 5.12 ± 1.02 | 9.19 ± 0.7 |
| **PCME** | 1.7 ± 0.65 | 5.15 ± 0.56 | 8.28 ± 2.13 | 1.7 ± 0.65 | 5.15 ± 0.56 | 8.28 ± 2.13 |
| **PCME (BERT)** | 1.7 ± 0.65 | 5.44 ± 0.76 | 9.16 ± 1.55 | 1.7 ± 0.65 | 5.44 ± 0.76 | 9.16 ± 1.55 |
| **Ours** | **1.74 ± 0.75** | **12.03 ± 0.37** | **19.14 ± 1.56** | **4.57 ± 1.45** | **13.11 ± 3.02** | **20.04 ± 2.47** |
| **Ours w/ Trace** | **1.17 ± 0.83** | **8.85 ± 1.9** | **14.85 ± 3.03** | 3.42 ± 0.6 | **10.03 ± 0.35** | **16.36 ± 2.08** |
|        | bio-4          | dental         | ml-1           | psy-1           |
|--------|----------------|----------------|----------------|----------------|
|        | Figure-to-Text | Text-to-Figure | Figure-to-Text | Text-to-Figure |
|        | Recall@1       | Recall@5       | Recall@10      | Recall@1       | Recall@5       | Recall@10      | Recall@1       | Recall@5       | Recall@10      |
| Random | 0.77 ± 0.44    | 2.15 ± 0.45    | 4.62 ± 1.04    | 0.77 ± 0.21    | 2.93 ± 0.98    | 5.84 ± 1.13    | 0.29 ± 0.21    | 0.92 ± 0.29    | 1.67 ± 0.28    |
| CLIP   | 0.32 ± 0.46    | 2.48 ± 0.16    | 4.95 ± 0.83    | 0.16 ± 0.23    | 1.88 ± 0.81    | 5.16 ± 1.5     | 0.23 ± 0.08    | 0.98 ± 0.23    | 1.85 ± 0.32    |
| PVSE   | 1.7 ± 1.44     | 4.75 ± 1.41    | 7.82 ± 1.96    | 2.17 ± 1.18    | 4.31 ± 1.25    | 6.45 ± 1.62    | 0.29 ± 0.08    | 1.44 ± 0.19    | 2.65 ± 0.26    |
| PVSE (BERT) | 1.08 ± 0.58 | 2.61 ± 0.57    | 5.07 ± 0.09    | 1.22 ± 0.75    | 3.52 ± 0.72    | 5.66 ± 1.61    | 0.64 ± 0.31    | 1.57 ± 0.65    | 2.6 ± 0.32     |
| PCME   | 1.86 ± 1.98    | 3.39 ± 1.55    | 4.92 ± 1.54    | 1.86 ± 1.98    | 3.39 ± 1.55    | 4.92 ± 1.54    | 0.23 ± 0.08    | 0.86 ± 0.13    | 1.73 ± 0.41    |
| PCME (BERT) | 0.62 ± 0.22 | 1.23 ± 0.57    | 3.99 ± 1.17    | 0.62 ± 0.22    | 1.23 ± 0.57    | 3.99 ± 1.17    | 0.23 ± 0.08    | 0.86 ± 0.23    | 1.67 ± 0.34    |
| Ours   | 4.28 ± 2.04    | 12.22 ± 6.66   | 18.5 ± 9.12    | 2.9 ± 1.72     | 11.79 ± 5.52   | 20.1 ± 6.1     | 0.63 ± 0.29    | 2.72 ± 0.23    | 6.18 ± 0.53    |
| Ours w/ Trace | 3.67 ± 1.82 | 12.07 ± 5.46   | 19.9 ± 6.82    | 2.29 ± 0.97    | 12.68 ± 5.64   | 21.88 ± 7.02   | 0.69 ± 0.23    | 3.28 ± 1.04    | 6.16 ± 1.1     |
|        | 0.63 ± 0.29    | 2.72 ± 0.23    | 6.18 ± 0.53    | 1.15 ± 0.16    | 5.31 ± 0.25    | 8.36 ± 1.45    | 0.8 ± 0.39     | 3.28 ± 0.69    | 5.88 ± 0.58    |
|        | 0.82 ± 0.05    | 4.76 ± 1.93    | 7.89 ± 1.87    | 1.15 ± 0.16    | 5.31 ± 0.25    | 8.36 ± 1.45    | 0.29 ± 0.21    | 0.92 ± 0.29    | 1.67 ± 0.28    |
|        | 1.22 ± 0.3     | 3.71 ± 0.89    | 6.2 ± 1.84     | 1.15 ± 0.16    | 5.31 ± 0.25    | 8.36 ± 1.45    | 0.8 ± 0.39     | 3.28 ± 0.69    | 5.88 ± 0.58    |

|        | Figure-to-Text | Text-to-Figure |
|--------|----------------|----------------|
|        | Recall@1       | Recall@5       | Recall@10      | Recall@1       | Recall@5       | Recall@10      | Recall@1       | Recall@5       | Recall@10      |
| Random | 4.48 ± 4.78    | 11.1 ± 6.21    | 21.22 ± 2.19   | 4.15 ± 1.35    | 15.36 ± 1.05   | 26.73 ± 1.25   | 2.68 ± 2.34    | 13.38 ± 2.66   | 22.35 ± 2.92   |
| CLIP   | 4.05 ± 3.89    | 13.22 ± 3.03   | 30.03 ± 5.88   | 2.68 ± 2.34    | 13.38 ± 2.66   | 22.35 ± 2.92   | 5.07 ± 2.48    | 17.98 ± 1.51   | 35.8 ± 1.29    |
| PVSE   | 3.99 ± 0.86    | 16.71 ± 4.75   | 29.65 ± 4.62   | 5.16 ± 3.59    | 20.46 ± 3.25   | 34.84 ± 2.33   | 4.16 ± 1.39    | 15.68 ± 2.66   | 30.92 ± 9.63   |
| PVSE (BERT) | 5.71 ± 2.87 | 18.87 ± 3.56   | 27.79 ± 3.23   | 4.16 ± 1.39    | 15.68 ± 2.66   | 30.92 ± 9.63   | 4.16 ± 1.39    | 14.46 ± 7.45   | 26.93 ± 10.49  |
| PCME   | 5.08 ± 2.49    | 14.75 ± 1.36   | 26.29 ± 3.24   | 9.38 ± 5.52    | 32.4 ± 1.45    | 43.52 ± 5.59   | 7.51 ± 3.75    | 20.83 ± 6.17   | 37.8 ± 5.6     |
| PCME (BERT) | 4.16 ± 1.39 | 13.54 ± 6.14   | 26.93 ± 10.49  | 7.51 ± 3.75    | 20.83 ± 6.17   | 37.8 ± 5.6     | 7.51 ± 3.75    | 20.83 ± 6.17   | 37.8 ± 5.6     |

The tables compare the performance of different methods on various datasets, showing Recall@1, Recall@5, and Recall@10 for both Figure-to-Text and Text-to-Figure tasks.
|               | Figure-to-Text | Text-to-Figure |
|---------------|----------------|---------------|
|               | Recall@1       | Recall@5      | Recall@10      | Recall@1  | Recall@5  | Recall@10 |
| Random        | 4.48 ± 4.78    | 11.1 ± 6.21   | 21.22 ± 2.19   | 0.44 ± 0.62| 5.96 ± 2.95| 12.74 ± 4.36|
| CLIP          | 4.05 ± 3.89    | 13.22 ± 3.03  | 30.03 ± 5.88   | 1.62 ± 1.46| 5.77 ± 1.85| 14.12 ± 0.88|
| PVSE          | 3.99 ± 0.86    | 16.71 ± 4.75  | 29.65 ± 4.62   | 3.47 ± 2.08| 11.2 ± 2.34| 19.22 ± 1.49|
| PVSE (BERT)   | **5.71 ± 2.87**| **18.87 ± 3.56**| **27.79 ± 3.23**| **4.47 ± 0.6**| **11.56 ± 1.24**| **18.26 ± 2.92**|
| PCME          | 5.08 ± 2.49    | 14.75 ± 1.36  | 26.29 ± 3.24   | 2.18 ± 2.24| 8.91 ± 3.03| 17.98 ± 2.88|
| PCME (BERT)   | 4.16 ± 1.39    | 13.54 ± 6.14  | 26.93 ± 10.49  | 1.83 ± 0.76| 8.63 ± 3.26| 15.94 ± 6.21|
| Ours          | **2.27 ± 3.21**| **19.5 ± 0.76**| **38.23 ± 2.51**| **1.36 ± 1.08**| **14.89 ± 7.3**| **26.92 ± 5.74**|
| Ours w/ Trace | **3.39 ± 1.54**| **19.18 ± 3.81**| **33.78 ± 4.26**| **2.72 ± 2.15**| **16.06 ± 0.29**| **27.66 ± 2.79**|

Table 6: Speaker-wise results for Figure-to-Text and Text-to-Figure retrieval. PolyViLT consistently outperforms previous baselines.
### G Keyword Identifiability

| PolyViLT r@10   | tfidf rank |
|-----------------|------------|
|                 | <5  | 5 -10 | 10 - 30 | 30 - 50 |
| Text-to-Figure  | 0.236 | 0.2  | 0.122  | 0.132  |
| Figure-to-Text  | 0.249 | 0.22 | 0.066  | 0.124  |

Table 7: Recall@10 scores for Keyword Identifiability measured by TF-IDF ranks

Specifically for figures which contain text, which consists of 54.9% of our dataset, there are many cases where the pairing between text and figures can be easily found by identifying the keyword and finding its existence in the figure or the spoken language. Naively finding the existence of identical words in two instances is trivial and could lead to incorrect retrievals. The core challenge lies in correctly identifying the keyword that defines the slide segment.

In order to understand the importance of identifying the keyword and how our model performs for text-inclusive figures, we measure the term frequency–inverse document frequency (or tf-idf) of each word in the spoken language, except stopwords which are filtered out. The words are then ranked according to their tf-idf values. We iterate through each word, find the words that also exist in the OCR output of the figure and extract the word with the lowest tf-idf rank. Under this condition, if the tf-idf rank for a word is 5, this can be intuitively seen as the fifth most important keyword that defines the slide. Simply stated, if the tf-idf rank of a word is low, the keyword can be easily detected in the slide and the spoken language. On the other hand, if the tf-idf rank of a word is high, this implies that the keyword is hard to detect.

In Table 7 we measure the recall@10 score conditioned on tf-idf ranks, which indicates how well PolyViLT does under varying levels of difficulty of identifying the keyword. PolyViLT’s struggles for cases with easier keyword identifiability and suffers even more with harder cases. This calls for a need for PolyViLT to effectively address easier cases, via using tf-idf directly as a feature, and relying more on the vision when the keyword is not easily identifiable.

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²Note that this method of retrieval is intractable with more number of words and documents
## Long Range Sequence and OOV Tokens

|        | (a) Length of Spoken Language | (b) Number of Subwords |
|--------|------------------------------|------------------------|
| **CLIP** |                              |                        |
| $r@10$ | $<100$                       | 100 - 200              | 200 - 400               | 400 - 600               | 600+        | $<10$       | 10 - 20      | 20 - 30      | 30 - 50      |
| Figure-to-Text | 0.0447                      | 0.0465                 | 0.0567                 | 0.0676                 | 0.175       | 0.065       | 0.062       | 0.0543       | 0.0619       |
| Text-to-Figure | 0.0793                      | 0.0662                 | 0.0599                 | 0.0571                 | 0.14        | 0.0704      | 0.055       | 0.0498       | 0.0473       |

| **PVSE** |                              |                        |
| $r@10$ | $<100$                       | 100 - 200              | 200 - 400               | 400 - 600               | 600+        | $<10$       | 10 - 20      | 20 - 30      | 30 - 50      |
| Figure-to-Text | 0.0779                      | 0.0777                 | 0.0644                 | 0.0901                 | 0.0928      | 0.0973      | 0.0842      | 0.0656       | 0.0667       |
| Text-to-Figure | 0.0901                      | 0.116                  | 0.1063                 | 0.1013                 | 0.0814      | 0.108       | 0.0839      | 0.0602       | 0.084        |

| **PCME** |                              |                        |
| $r@10$ | $<100$                       | 100 - 200              | 200 - 400               | 400 - 600               | 600+        | $<10$       | 10 - 20      | 20 - 30      | 30 - 50      |
| Figure-to-Text | 0.0342                      | 0.1301                 | 0.082                  | 0.0733                 | 0.053       | 0.0744      | 0.0556      | 0.0617       | 0.0271       |
| Text-to-Figure | 0.0342                      | 0.1301                 | 0.082                  | 0.0752                 | 0.0536      | 0.076       | 0.0518      | 0.0603       | 0.0309       |

Table 8: For all competitive baselines, performance (a) peaks at 100-200 words then drops with increasing length of spoken language and (b) drops with increasing number of subwords
I Qualitative Cases of Failure

| Source Figure | Ground Truth Text | Retrieved Text |
|---------------|-------------------|----------------|
| ![Figure](source.png) | types again here's a side view notice the spine and saw the spinous processes it's much larger thicker inner thigh just for a lot of these muscles these larger muscles to come and test you same thing with the transverse process very different than what we had over here there's no ribs over here over here so this is the inferior articular process infested over here that you see here is a superior articular process over there you can see the faceting fortunately | so here you go everything you see in the midline of the body this is your axial skeleton so all your limbs they make up your appendicular skeleton so if you look over here you have your skull okay and then you have your your ribcage right this is your thoracic cage also is called and the thoracic cage again is made up of your customers this is ribs the sternum and the backbones all right they also cause posteriorly the castles the articulate with the um t1 through t12 your vertebral column the bones of the vertebral column so yeah now we're going to be looking at all this stuff in detail as we move through the course to this chapter actually |
| ![Figure](source.png) | types again here's a side view notice the spine and saw the spinous processes it's much larger thicker inner thigh just for a lot of these muscles these larger muscles to come and test you same thing with the transverse process very different than what we had over here there's no ribs over here over here so this is the inferior articular process infested over here that you see here is a superior articular process over there you can see the faceting | let's move further you go you can see again in this picture then anterior longitudinal ligament very clearly notice it's a very broad it's a large strong ligament over here and comparatively the posterior longitudinal ligament much smaller so it's much weaker this is strong one this is the weak one and yes you can see the this is the body of the vertebrae the transverse processes the vertebrae over here |
| ![Figure](source.png) | fluid so in this illustration we see a synovial joint so here are the two articulating bones and you can see that the articular bones there are lined with this articular cartilage at the articulating surface now we see this fibrous layer here that the outer fibrous layer and then we have this inner synovial membrane that forms the articular capsule the spaces between within this capsule it constitutes the joint cavity and is within this joint cavity we will find the synovial fluid we also see this outer get over here not this would be an example of this capsular ligaments and this is a it thickens the the fibrous layer to reinforce and straighten this joint | women so when you look over here this is scoliosis notice how you have this axis you have a lateral rotation of your thoracic spine over here too let's push more towards this side to ensure that the left side and it is towards the right and then you look over here this is this kyphosis this is over here so this the hunchback then if you look over here in lordosis again you have this access anterior curvature of the your lumbar spine so again over here you seeing this in the lumbar spine kyphosis generally speaking you'll tend to see in the the thoracic region thoracic spine in this of scoliosis also again commonly again you can see |

Figure 8: Figure-to-Text: Failure Case for Anat-1 (top-1 retrieval result shown on right)
so here you go everything you see in the midline of the body this is your axial skeleton so all your limbs they make up your appendicular skeleton so if you look over here you have your skull okay and then you have your your ribcage right this is your thoracic cage also is called and the thoracic cage again is made up of your customers this is ribs the sternum and the backbones all right they also cause posteriorly the castles the articulate with the um t1 through t12 your vertebral column the bones of the vertebral column so yeah now we're going to be looking at all this stuff in detail as we move through the course to this chapter actually

formed the side here we're looking at a scanning electron micrograph and you can see this fibermesh that's over here and within this fiber mesh you can see all the red blood cells that are trapped

fluid so in this illustration we see a synovial joint so here are the two articulating bones and you can see that the articular bones there are lined with this articular cartilage at the articulating surface now we see this fibrous layer here that the outer fibrous layer and then we have this inner synovial membrane that forms the articular capsule the spaces between within this capsule it constitutes the joint cavity and is within this joint cavity we will find the synovial fluid we also see this outer get over here not this would be an example of this capsular ligaments and this is a it thickens the the fibrous layer to reinforce and straighten this joint

Figure 9: Text-to-Figure: Failure Cases for Anat-1 (top-1 retrieval result shown on right)
process now we get up to the distal tube which is again next to the proximal tube and now you see more salt being pulled out more water being pulled out and then you get potassium hydrogen and proton ions in this case and again concentrations regulates those concentrations and then the ions contributes to the pH regulation in this case so that it stays neutral pH

that that an issue so like i said angiotensin raises the blood pressure and decreases the blood flow in the capillaries in the kidneys and then like i said if you have chronic high blood pressure some of these drugs that we take actually will rot block this a 2 or this angiotensin ii and because of that it will cause the kidneys to lower the amount of water tension and then lower the blood pressure because again more water less water in the blood the blood pressure goes down and so again that gets it warranted dehydration state and so those that are on hypertension a lot of times will then complain that they get thirsty a lot because of that and same with diabetes because you're getting more sugar in the blood and that stuff and that's a whole nother another situation

in detail how this all works now with the hydrostatic skeleton this is fluid under the pressure of a close body compartment allows the muscles to contract and extend and so an essentially this works kind of like how her esophagus does with peristalsis and so again the use these rhythmic contractions using the fluid that allows them to extend and contract the muscle and allows it to move through the soil and so this is the main type of skeleton that most nigerians flatworms nematodes and annelids use to move through either water or soil in these situations and again under the hydrostatic skeleton glands in these situations now most of these systems are based on the feedback loops in that and so you'll see that again typically what you see is either get a positive feedback or negative feedback so you either turn something on or shut something down depending on whether it is a response is needed and so the example that i have here is the negative feedback with calcium and so again typically in homeostasis you have normal calcium in the blood but if the calcium levels get too high your thyroid will release the sinkhole calcitonin and that will cause an increase of calcium into the bone which causes again a decrease in the amount of calcium in the intestines
now in most animals osmoregulation in metabolic waste disposal rely on transport epithelia and so again these are cells that help move things across membranes and so that's going to be the key step so when we talk about blood and capillaries again you're going to have these solutes going across the movement along with water and that's where you're going to see this and again these cells are specialized removing solutes across in controlled amounts across specific things and they have carrier protein...

process now we get up to the distal tube which is again next to the proximal tube and now you see more salt being pulled out more water being pulled out and then you get potassium hydrogen and proton ions in this case and again concentrations regulates those concentrations and then the ions contributes to the ph regulation in this case so that it stays neutral

place where you see koreans playing a big role so how are action potentials generated so we can measure the action potential by again using this the system and so you have this microelectrode attached to the neuron and we can measure with the reference electrode what is going on inside the inside the neuron now changes in the membrane potential occur because the neurons contain gated ion channels either open and closed due to stimuli and the voltage-gated ion channel opens and closes in response to the shift of the voltage across the plasma membrane...

| Source Text                                                                 | Ground Truth Figure                                      | Retrieved Figure                                       |
|-----------------------------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------------------|
| now in most animals osmoregulation in metabolic waste disposal rely on      | ![Ground Truth Figure](image1.png)                       | ![Retrieved Figure](image2.png)                       |
| transport epithelia and so again these are cells that help move things      |                                                           |                                                        |
| across membranes and so that's going to be the key step so when we talk    |                                                           |                                                        |
| about blood and capillaries again you're going to have these solutes       |                                                           |                                                        |
| going across the movement along with water and that's where you're going    |                                                           |                                                        |
| to see this and again these cells are specialized removing solutes across   |                                                           |                                                        |
| in controlled amounts across specific things and they have carrier protein...|                                                           |                                                        |
| process now we get up to the distal tube which is again next to the proximal| ![Ground Truth Figure](image3.png)                       | ![Retrieved Figure](image4.png)                       |
| tube and now you see more salt being pulled out more water being pulled out |                                                           |                                                        |
| and then you get potassium hydrogen and proton ions in this case and again  |                                                           |                                                        |
| concentrations regulates those concentrations and then the ions contributes |                                                           |                                                        |
| to the ph regulation in this case so that it stays neutral                  |                                                           |                                                        |
| place where you see koreans playing a big role so how are action potentials | ![Ground Truth Figure](image5.png)                       | ![Retrieved Figure](image6.png)                       |
| generated so we can measure the action potential by again using this the    |                                                           |                                                        |
| system and so you have this microelectrode attached to the neuron and we    |                                                           |                                                        |
| can measure with the reference electrode what is going on inside the inside |                                                           |                                                        |
| the neuron now changes in the membrane potential occur because the neurons  |                                                           |                                                        |
| contain gated ion channels either open and closed due to stimuli and the    |                                                           |                                                        |
| voltage-gated ion channel opens and closes in response to the shift of the  |                                                           |                                                        |
| voltage across the plasma membrane...                                      |                                                           |                                                        |

Figure 11: Text-to-Figure: Failure Cases for Bio-1 (top-1 retrieval result shown on right)
alright so another thing we like to do in both surgical extraction and after a simple extraction is irrigation so here is a mono jet syringe and we can load this up with sterile saline in order to clean out the extraction site so we use a steady stream of sterile saline or water during bone removal for a surgical extraction and it prevents heat generation from the spinning bird that can damage bone it also increases the efficiency of the surgical bone of the surgical birth and is because it washes away the chips of bone and provides lubrication for the surgical bird so like i mentioned before you want to irrigate during surgical removal of bone and at the completion of any extraction to flush the socket of any debris a infectious or inflamed tissue you can also give a patient this to take home with them for gentle warm salt water rinses and flushing out of the healing socket at home i think that can be a very useful tool to use at for home care

Figure 12: Figure-to-Text: Failure Case for dental (top-1 retrieval result shown on right)

all right and so those were the hand instruments we talked about sickle scalars and curettes and now we can talk about ultrasonic scalars which are used for tenacious calculus is calculus that can be harder to remove now you can also use hand instruments to get to get tenacious calculus off that's for sure but for the board exam just remember that they like to test that ultrasonic scalars can specifically be used for some tough to get calculus there are contraindicated for patients with pacemakers infectious diseases spread by aerosol and at risk for respiratory disease that's because they spit out a lot of water and in terms of the the pacemaker here electronic dental instruments like ultrasonic scalars and also apex locator has used in endodontics could potentially interfere with pacemakers because they use electrical impulses to maintain proper heart rhythm so that's just an important thing to note there are two different main types of ultrasonics there is a magnetic stricte vulture sonic liner and then a base can be used for metal restorations and when liner is used so it goes over the liner in order to protect it from being resorbed and washed out the base also provides thermal protection and can distribute local stress across all the underlying dentin resin-modified glass ionomer is what this stands for is frequently used as a base pitch or bond is our example here

could result in congenitally missing or supernumerary teeth if it occurs early on but more likely you're going to see a cyst oh don toma gemination or fusion or dens and dente depending on the amount of cell differentiation and that has occurred
so there are really two phases of the orthodontic wire and that's activation which is also known as loading and that refers to the amount of force applied to engage the wire into the brackets lat so it's engaging the wire into the brackets lat and then tying it into place deactivation or unloading is letting the wire return back to its original shape and it's the amount of force that the wire applies to the tooth to get back to its original shape so based on how the wire is deflected when it's tied into these brackets it will apply a force to them because the wire wants to return back to its original shape because of its inherent elasticity so in this example the wire originally started out as a straight line a straight horizontal line and so when we deflected up here we can't quite get it into the brackets

apex ford integer assist now we have the radial lucency which is attached to the oej or the cemento and will junction where the enamel meets the cementum of the root and you can see how this radiolucency comes neatly attached to that point of the tooth now it's most common with canines and third molars and here this looks like it could be a second molar or third molar let's just say this is in fact a wisdom tooth and it's an accumulation of fluid between the crown and the reduced enamel epithelium which if you notice

| Source Text                                                                 | Ground Truth Image | Retrieved Image |
|----------------------------------------------------------------------------|--------------------|-----------------|
| so there are really two phases of the orthodontic wire and that's activation which is also known as loading and that refers to the amount of force applied to engage the wire into the brackets lat so it's engaging the wire into the brackets lat and then tying it into place deactivation or unloading is letting the wire return back to its original shape and it's the amount of force that the wire applies to the tooth to get back to its original shape so based on how the wire is deflected when it's tied into these brackets it will apply a force to them because the wire wants to return back to its original shape because of its inherent elasticity so in this example the wire originally started out as a straight line a straight horizontal line and so when we deflected up here we can't quite get it into the brackets | ![Ground Truth Image](image1.png) | ![Retrieved Image](image2.png) |
| apex ford integer assist now we have the radial lucency which is attached to the oej or the cemento and will junction where the enamel meets the cementum of the root and you can see how this radiolucency comes neatly attached to that point of the tooth now it's most common with canines and third molars and here this looks like it could be a second molar or third molar let's just say this is in fact a wisdom tooth and it's an accumulation of fluid between the crown and the reduced enamel epithelium which if you notice | ![Ground Truth Image](image3.png) | ![Retrieved Image](image4.png) |

Figure 13: Text-to-Figure: Failure Cases for dental (top-1 retrieval result shown on right)
and beyond vqa there's a bunch of other data sets most of them similar in vain here's a reference you can put more of them if you're interested is there are image-based qa and

so given all these real-world tasks we've tried to group our best we tried our best to group these applications into seven groups these are by no means exhaustive and this is by no means a perfect categorization but we like to share some of this categorization with you so that helps you localize what area you want to work on for your research project and also the datasets that are within this area the first one is that on effective recognition affective computing building these computers are able to understand these human-centric behaviors like emotion and sentiment media description for image and video captioning multimodal qa which for the localizers need a description by...

that and if you were to do on supervised i didn't put a slide for his but they are some very well-established algorithms that you can do to also study how to learn and put some kind of superb vision on the z so that eventually you keep the similarity as close to each other and there's quite a few of these note tuvok being one of them

| Source Figure | Ground Truth Text | Retrieved Text |
|---------------|-------------------|----------------|
| ![Figure 1](image1.png) | these saddle point i'm not giving as much in this kind of on purpose because now these days there are a lot of these that have been in a lot of districts have been included in these different libraries so you can | and beyond vqa there's a bunch of other data sets most of them similar in vain here's a reference you can put more of them if you're interested is there are image-based qa and |
| ![Figure 2](image2.png) | so let's summarize we've got two mvps we've seen how an agent with taking actions and going into different states and environment and observing rewards is a very general framework that i capsule has many of the real world reasoning tasks we know that we've seen that you know the goal of the agent is to maximize its cumulative reward x a discount factor and you want to learn the best policy organized over all possible policies that best maximizes your primitive reward each of these policies will define a particular distribution over actions that the agent should take from different states so here are the here's the main goal of reinforcement learning | so given all these real-world tasks we've tried to group our best we tried our best to group these applications into seven groups these are by no means exhaustive and this is by no means a perfect categorization but we like to share some of this categorization with you so that helps you localize what area you want to work on for your research project and also the datasets that are within this area the first one is that on effective recognition affective computing building these computers are able to understand these human-centric behaviors like emotion and sentiment media description for image and video captioning multimodal qa which for the localizers need a description by... |
| ![Figure 3](image3.png) | distance between two values to these position is not as informative as the direction of it what it means the fact that dog is here here instead of here here here here are the only reason it is at this position is that it happened more often in or coppers it happened hundred to eighteen times here and maybe 10 times here what is important is more the ratio between them is that the most respond the fact that it happened really often is not as much of a like a good descriptor of meaning of a word but the ratio between use and get is more useful so the angle and so like the distant itself just mean that dog was used more often the word in that corpus what | that and if you were to do on supervised i didn't put a slide for his but they are some very well-established algorithms that you can do to also study how to learn and put some kind of superb vision on the z so that eventually you keep the similarity as close to each other and there's quite a few of these note tuvok being one of them |

Figure 14: Figure-to-Text: Failure Case for ml-1 (top-1 retrieval result shown on right)
that and if you were to do on supervised i didn't put a slide for his but they are some very well-established algorithms that you can do to also study how to learn and put some kind of superb vision on the z so that eventually you keep the similarity as close to each other and there's quite a few of these note tuvok being one of them

so given all these real-world tasks we've tried to group our best we tried our best to group these applications into seven groups these are by no means exhaustive and this is by no means a perfect categorization but we like to share some of this categorization with you so that helps you localize what area you want to work on for your research research project and also the datasets that are within this area the first one is that on effective recognition affective computing building these computers are able to understand these human-centric behaviors like emotion and sentiment media description for image and video captioning multimodal qa which for the localizers need a description by only answering a question by only providing an answer about a specific question target to one specific area of the image multimodal navigation which really combines these aspects of reinforcement learning and robotics with understanding language and vision

bi-directional you can do bi-directional and multiple layers of bi-directional elmo had two of them

| Source Text | Ground Truth Figure | Retrieved Figure |
|-------------|---------------------|------------------|
| **Figure 15:** Text-to-Figure: Failure Cases for ml-1 (top-1 retrieval result shown on right) | ![Ground Truth Figure](image1.png) | ![Retrieved Figure](image2.png) |
for most people once they get married
one of the next things that they look for
to is having babies or starting their own
families we know that in today's western
societies couples are having fewer and
fewer children in part that's because of
economics and you would think that oh
it's because it's more expensive actually
it's the opposite it's the fact that they are
working and so less children is easier to
take care of but also the fact that
basically our children are living when we
had high death rates of children you
would have multiple children in hopes of
getting a few to adulthood but today we
pretty much figure our children are
going to make it to adulthood we don't
sit there and think as some people used
to have to worry about is that 30 to 40 to
50% of their children weren't going to
make it to adulthood so 50% of my
children are going to make it to
adulthood

by the time they're to the child's growth
is really slow down and quite often they
become much more finicky about what
they want to eat the good thing is is that
they still get all their nutrition generally
mostly what people will say to you if
you're talking to some of the experts we
just tried to have the widest variety of
diet that you can when the child is under
2 because the more they're introduced
to new foods and other items the more
likely they'll be eating it when they're too
so if they peas one there's probably a
good chance they're going to eat peas a
to the problem is that we tend to maybe
not feed the best food when they're
younger

our satisfaction with a job is absolutely
directly related to our age meaning is
what we're looking for from the job will
change as we grow older this chapter is
mostly talking about middle-aged
worker so let's kind of look at that as a
specific and one thing is that in middle
age as we said you're looking for a job
for union with others and to help you
within sort of your life as you're having it
at the moment so this intrinsic reward
becomes much more important than the
extrinsic rewards and intrinsic means
inside of yourself are you satisfied with
what you're doing does you find it
interesting are you challenged enough
or challenge too much you might want
to say so as we get older we do want
certain things to help us with having a
satisfactory life and that includes our job
so as you begin to have children you
might want to have a more flexible
lifestyle

| Source Figure | Ground Truth Text | Retrieved Text |
|---------------|-------------------|----------------|

Figure 16: Figure-to-Text: Failure Case for Psy-2 (top-1 retrieval result shown on right)
theory of attachment suggests that children come the world biologically programmed to form attachment with others this is because it helps them survive those who seem to be attached to somebody we're more likely to receive comfort and protection and they absolutely have shown that they're more likely to survive into adulthood this is not just seen in humans but this is also seen in the great apes scimpanzees the mammals so when we have an attachment it helps our survival so infants produce this sort of innate social release of plea such as crying and smiling that sort of stimulates is an 8 caregiver response from us as adults now by the way the reason i'm saying caregiver is that it isn't always the mother i don't want this thought to be in your head that had has to be the mother this can be the father this can be the grandparent this can be an adopted person it doesn't have to be a biologically the mother so we use the word caregiver to be a more general type of scenario

for most people once they get married one of the next things that they look for is having babies or starting their own families we know that in today's western societies couples are having fewer and fewer children in part that's because of economics and you would think that oh it's because it's more expensive actually it's the opposite it's the fact that they are working and so less children is easier to take care of but also the fact that basically our children are living when we had high death rates of children you would have multiple children in hopes of getting a few to adulthood…

| Source Text | Ground Truth Figure | Retrieved Figure |
|-------------|---------------------|-------------------|
| theory of attachment suggests that children come the world biologically programmed to form attachment with others this is because it helps them survive those who seem to be attached to somebody we're more likely to receive comfort and protection and they absolutely have shown that they're more likely to survive into adulthood this is not just seen in humans but this is also seen in the great apes scimpanzees the mammals so when we have an attachment it helps our survival so infants produce this sort of innate social release of plea such as crying and smiling that sort of stimulates is an 8 caregiver response from us as adults now by the way the reason i'm saying caregiver is that it isn't always the mother i don't want this thought to be in your head that had has to be the mother this can be the father this can be the grandparent this can be an adopted person it doesn't have to be a biologically the mother so we use the word caregiver to be a more general type of scenario | | |
| for most people once they get married one of the next things that they look for is having babies or starting their own families we know that in today's western societies couples are having fewer and fewer children in part that's because of economics and you would think that oh it's because it's more expensive actually it's the opposite it's the fact that they are working and so less children is easier to take care of but also the fact that basically our children are living when we had high death rates of children you would have multiple children in hopes of getting a few to adulthood… | | |

Figure 17: Text-to-Figure: Failure Cases for Psy-2 (top-1 retrieval result shown on right)