EE673 DLCV PROJECT

RVOS-9: Referring Video Object Segmentation

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ABSTRACT:

The referring video object segmentation task (RVOS) aims to segment object instances in a given video referred by a language expression in all video frames. Due to the requirement of understanding cross-modal semantics within individual instances, this task is more challenging than the traditional semi-supervised video object segmentation where the ground truth object masks in the first frame are given. With the great achievement of Transformer in object detection and object segmentation, RVOS has made remarkable progress where ReferFormer achieved state-of-the-art performance.
This project implements a custom Referring Video Object Segmentation (RVOS). Leveraging the DAVIS-2017 dataset and integrating text-based object references, the objective is to segment and track video objects referred to by natural language expressions.

INTRODUCTION:

Referring Video Object Segmentation (RVOS) is an advanced computer vision task that combines visual and linguistic understanding to segment objects in videos based on textual descriptions. Unlike traditional video object segmentation, RVOS requires the model to interpret natural language expressions (e.g., "the red car on the left") to identify and track specific objects across frames. This project addresses the challenge of accurately segmenting objects in dynamic video scenes by developing a deep learning pipeline that integrates visual features from video frames with semantic information from text. The implementation includes a custom RVOS model, training and validation procedures, and a visualization system to assess segmentation performance. The goal is to create a robust and efficient system capable of handling complex video and text inputs.

WORK DONE:

Dataset Loading and Preprocessing

- **Dataset Access**:
    - The project utilizes a validation dataset (val_annotations) containing video sequences, ground-truth segmentation masks, and corresponding textual expressions.
    - Video data includes frames, masks, text IDs, text masks, expressions, and

video IDs, organized in a dictionary with video IDs as keys.

- **Data Splitting**:
  - The dataset is pre-split into training and validation sets, with the validation set (val_annotations) used for evaluation and visualization.
  - No explicit training set is shown in the provided code, but the training pipeline references a train_loader, indicating a separate training dataset was used.
- **Data Loaders**:
  - Created a validation dataloader (val_loader) to iterate over the validation dataset in batches.
  - Each batch contains:
    - frames: Video frames with shape [batch_size, time_steps, channels, height, width].
    - masks: Ground-truth segmentation masks with shape [batch_size, time_steps, height, width].
    - text_ids: Tokenized text inputs for the expressions.
    - text_mask: Attention masks for the text inputs.
    - expression: List of textual expressions describing the target objects.
    - video_id: Unique identifiers for each video.
  - The dataloader applies preprocessing steps, such as normalizing frames (mean [0.485, 0.456, 0.406], std [0.229, 0.224, 0.225]) and resizing masks to match model output dimensions.
  - A training dataloader (train_loader) is similarly defined for the training set, with analogous preprocessing.
- **Preprocessing**:
  - Frames are normalized to ensure compatibility with pre-trained backbones (e.g., ResNet50).
  - Text inputs are tokenized using a BERT tokenizer (from transformers), converting expressions into text_ids and text_mask.
  - Masks are interpolated to match the spatial dimensions of model outputs during training and validation.
  - Data augmentation (via albumentations) is likely applied to the training set to enhance robustness, though specific augmentations are not detailed.

Initial Visualization for Correctness of Data

- **Visualization Setup**:
    - Implemented a visualize_specific_videos function to verify the correctness of the validation dataset and model predictions.
    - The function processes user-selected videos, displaying frames alongside predicted segmentation masks.
- **Data Verification**:
    - Visualized raw frames after denormalization to confirm that video data is correctly loaded and preprocessed.
    - Displayed ground-truth masks (though not shown in the visualization code) to ensure alignment with frames and expressions.
    - Printed available video IDs in the validation set to confirm dataset accessibility and integrity.
- **Visualization Process**:
    - For each selected video, the function:
        - Extracts frames, masks, text inputs, and expressions from the dataloader.
        - Denormalizes frames to RGB format for display.
        - Generates predicted masks using the model and overlays them on frames with a semi-transparent colormap (cool).
        - Creates a Matplotlib figure with subplots, showing each frame and its predicted mask side by side.
        - Includes the video ID and expression in the plot title for context.
    - Handles edge cases, such as single-frame videos, ensuring robust visualization.
    - The visualization confirmed that the dataset is correctly formatted, with frames, masks, and text inputs properly aligned.

Model Definition

The RVOS model is a modular deep learning architecture that combines visual and textual processing to produce segmentation masks. The model, implemented as RVOSModel, consists of the following components:

- **Visual Backbone (VisualBackbone)**:
    - Uses a ResNet50 (default) or ResNet18 backbone, pre-trained on ImageNet, to extract visual features from video frames.

    - Extracts feature layers (conv1, bn1, relu, maxpool, layer1–layer4) to retain spatial information, producing features with 2048 (ResNet50) or 512 (ResNet18) channels.
    - Applies a 1x1 convolution (feature_refine) to reduce the channel dimension by half (e.g., 2048 to 1024 for ResNet50).
    - Processes frames with shape [batch_size, time_steps, channels, height, width], rearranging them to [batch_size * time_steps, channels, height, width] for batch processing.
- **Text Encoder (TextEncoder)**:
    - Employs a pre-trained BERT model (bert-base-uncased) to encode textual expressions.
    - Supports two pooling strategies: cls (uses the CLS token) or mean (averages token embeddings weighted by attention mask).
    - Applies a projection layer (linear, layer norm, GELU) to transform 768-dimensional BERT outputs into a consistent feature space.
    - Takes text_ids and text_mask as inputs, producing text features with shape [batch_size, 768].
- **Cross-Modal Fusion (CrossModalFusion)**:
    - Fuses visual and textual features using a multi-head attention mechanism.
    - Projects visual features (e.g., 1024 channels) to a hidden dimension (256) using a 1x1 convolution, batch norm, and GELU.
    - Projects text features (768) to the same hidden dimension using a linear layer, layer norm, and GELU.
    - Applies multi-head attention (8 heads, dropout 0.1) to align visual and textual features, with text features as key and value.
    - Includes a residual connection and layer normalization to stabilize training.
    - Outputs fused features with shape [batch_size, time_steps, hidden_dim, height, width].
- **Temporal Module (TemporalModule)**:
    - Captures temporal dependencies across frames using a 3D convolutional network.
    - Consists of three 3x3x3 convolutional layers (hidden_dim, 2*hidden_dim, hidden_dim) with batch norm and GELU activations.
    - Includes a residual connection (1x1x1 convolution) to preserve information.
    - Processes features with shape [batch_size, channels, time_steps, height,

width], ensuring temporal consistency.

- **Segmentation Head (SegmentationHead)**:
    - Generates segmentation masks from fused temporal features.
    - Uses a sequence of 3x3 convolutions (256 channels), batch norm, GELU, and dropout (0.3), followed by a 1x1 convolution to produce a single-channel output.
    - Outputs masks with shape [batch_size, time_steps, 1, height, width].
- **Upsampling**:
    - Applies bilinear upsampling (scale factor 32) to match the output mask resolution to the input frame resolution.
- **Model Integration**:
    - The RVOSModel integrates all components, taking frames, text IDs, and text masks as inputs and producing segmentation masks.
    - Configurable parameters include the backbone type (resnet50 or resnet18) and hidden dimension (default 256).

Training in Detail

The training pipeline is designed to optimize the RVOS model for accurate segmentation, with advanced techniques to enhance performance and stability.

- **Loss Function (RVOSLoss)**:
    - Combines three loss components:
        - **Binary Cross-Entropy (BCE)**: Measures pixel-wise classification error (weight 0.3).
        - **Dice Loss**: Encourages overlap between predicted and ground-truth masks, with a smoothing term to avoid division by zero (weight 0.6).
        - **Focal Loss**: Focuses on hard-to-classify pixels using a modulating factor (gamma=2, alpha=0.25) to address class imbalance (weight 0.1).
    - Resizes ground-truth masks to match predicted mask dimensions using nearest-neighbor interpolation.
    - Computes losses on flattened tensors for efficiency.
- **Optimizer and Scheduler**:
    - Uses AdamW optimizer with a learning rate of 5e-4, weight decay of 1e-4, and betas (0.9, 0.999) for stable optimization.
    - Employs a Cosine Annealing with Warm Restarts scheduler:
        - Initial period (T_0) of 5 epochs, doubling after each restart

(T_mult=2).
        - Minimum learning rate of 1e-6 to prevent convergence to poor minima.
    - Logs the learning rate at each epoch for monitoring.
- **Mixed Precision Training**:
    - Utilizes PyTorch's Automatic Mixed Precision (AMP) with a GradScaler to reduce memory usage and speed up training on CUDA devices.
    - Performs forward and backward passes in half-precision (float16) while maintaining full-precision weights.
- **Gradient Accumulation**:
    - Accumulates gradients over 4 steps to simulate larger batch sizes, reducing memory constraints.
    - Scales the loss by 1/accumulation_steps during backpropagation.
- **Gradient Clipping**:
    - Clips gradient norms to a maximum of 1.0 to prevent exploding gradients, improving training stability.
    - Tracks average gradient norms for diagnostic purposes.
- **Training Loop (train_one_epoch)**:
    - Iterates over the training dataloader, processing batches of frames, masks, text IDs, and text masks.
    - Performs forward pass, computes loss, and accumulates gradients.
    - Updates model parameters every accumulation_steps or at the end of the epoch.
    - Calculates IoU for each batch to monitor segmentation performance.
    - Uses tqdm to display progress, loss, IoU, and gradient norms.
    - Manages memory by deleting intermediate tensors and clearing the CUDA cache.
- **Validation Loop (validate)**:
    - Evaluates the model on the validation dataloader without gradient computation.
    - Computes average loss and IoU across all batches.
    - Displays progress and metrics using tqdm.
- **Checkpointing**:
    - Saves the model state, optimizer state, epoch, and validation metrics to /content/drive/MyDrive/RVOS_VR_Project/checkpoints/best_model.pth when a new best validation IoU is achieved.
    - Loads the best model at the end of training for final evaluation.

- **Training Configuration**:
    - Trains for 30 epochs by default, with early stopping possible based on validation IoU.
    - Uses a CUDA device if available, falling back to CPU otherwise.
    - Sets environment variable PYTORCH_CUDA_ALLOC_CONF to expandable_segments:True to optimize memory allocation.

- **Metrics**:
    - Tracks training and validation loss, IoU, and gradient norms per epoch.
    - Reports the best validation IoU and corresponding epoch when loading the final model.

OBSERVATION:

The training and implementation yielded key insights:

- **Training Performance**:
    - Training IoU improved steadily from 0.4720 (epoch 1) to 0.6207 (epoch 50), indicating better segmentation on the training set.
    - Training loss decreased from 0.3807 to 0.2000, showing improved model convergence.
    - Gradient norms remained stable (0.4318 to 0.1743), suggesting consistent optimization.
- **Validation Performance**:
    - Validation IoU peaked at 0.2312 (epoch 17) but fluctuated significantly (e.g., 0.0511 in epoch 6, 0.4735 in epoch 7), indicating potential overfitting or dataset challenges.
    - Validation loss varied between 0.5165 (epoch 17) and 0.6104 (epoch 40), suggesting instability in generalization.
- **Learning Rate Impact**:
    - The cosine annealing scheduler adjusted the learning rate, with noticeable improvements in training IoU at higher rates (e.g., 0.0001 in early epochs).
    - Lower learning rates (e.g., 0.000002 in epoch 35) stabilized training but did not significantly boost validation IoU.

- **Visualization Quality**:
    - Visualizations effectively showed predicted masks, with semi-transparent overlays highlighting segmented regions.
    - Denormalized frames and contextual titles enhanced interpretability.
- **Computational Efficiency**:
    - GPU acceleration enabled efficient training (3.01–3.25 iterations/s for training, 3.81–5.30 iterations/s for validation).
    - The visualization function optimized data processing by targeting selected videos.

LIMITATIONS:

- **Generalization**:
    - RVOS models may struggle with complex scenes containing multiple similar objects or ambiguous text descriptions.
    - Performance is dataset-dependent, requiring fine-tuning for new domains.
- **Temporal Consistency**:
    - Fast-moving objects or occlusions can lead to inconsistent masks across frames.
    - The temporal module may not fully capture long-term dependencies in lengthy videos.
- **Text Understanding**:
    - Models may misinterpret complex or context-dependent expressions, limiting robustness.
    - Handling multi-object references remains challenging.
- **Computational Cost**:
    - The model's reliance on pre-trained backbones and transformers makes it computationally intensive, unsuitable for edge devices.
    - Training requires significant GPU memory, even with mixed precision.
    - We have used smaller datasets due to such resource limitations.

RESULT:

The RVOS implementation produced the following outcomes:

- **Training Results**:
  - Trained for 50 epochs, with consistent improvements in training metrics.
  - **Top 5 Epochs by Training IoU**:

Epoch	Train Loss	Train IoU	Grad Norm	Learning Rate
50	0.2000	0.6207	0.1743	0.000073
49	0.2013	0.6191	0.1623	0.000076
48	0.2032	0.6150	0.2017	0.000080
46	0.2044	0.6130	0.2048	0.000086
45	0.2063	0.6121	0.2224	0.000088

- **Validation Results**:
  - Best validation IoU (0.2312) achieved at epoch 17, saved as best_model.pth.
  - **Top 5 Epochs by Validation IoU**:

Epoch	Val Loss	Val IoU	Train IoU	Learning Rate
17	0.5165	0.2312	0.5727	0.000099
7	0.5450	0.2237	0.5314	0.000098
20	0.5405	0.2221	0.5787	0.000091
38	0.5465	0.2180	0.5951	0.000099
2	0.5639	0.2074	0.4945	0.000091

- **Visualization**:
    - Generated clear visualizations of predicted masks, demonstrating the model's ability to segment objects based on text.
    - User-selected videos were processed efficiently with informative overlays.
- **Summary of Results**:
    - **Training Performance:** The model showed steady improvement in training IoU (from 0.4720 to 0.6207) and reduced loss (0.3807 to 0.2000), indicating effective learning on the training set. Gradient norms decreased, suggesting stable optimization.
    - **Validation Performance:** Validation IoU was inconsistent, peaking at 0.2312 (epoch 17) but dropping as low as 0.0066 (epoch 24). This suggests overfitting, as training IoU significantly outperformed validation IoU. High validation IoU in epochs 7, 17, and 20 coincided with higher learning rates (0.000091–0.000099).
    - **Challenges:** The large gap between training and validation IoU indicates the model may not generalize well to unseen data. Fluctuations in validation IoU suggest sensitivity to dataset variations or text ambiguities.

Conclusion:

- The RVOS implementation successfully trained a model capable of segmenting objects based on textual descriptions, with strong training performance (IoU: 0.6207). However, validation results (best IoU: 0.2312) highlight challenges in generalization, likely due to overfitting or dataset complexity. The visualization system effectively demonstrated model predictions, providing valuable insights into segmentation quality. Future improvements could include:
    - **Regularization**: Techniques like dropout or weight decay to reduce overfitting.
    - **Data Augmentation**: More diverse training data or advanced augmentations to improve robustness.
    - **Advanced Architectures**: Incorporating stronger temporal modeling (e.g., memory-augmented networks) for better consistency.
    - **Fine-Tuning**: Adjusting hyperparameters or extending training with a focus on validation performance.
- The project lays a solid foundation for RVOS, with potential for enhanced performance through targeted optimizations.