HERO: Hierarchical Encoder for Video+Language Omni-representation Pre-training

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* Equal Contribution
Vision + Language Pre-training

Vision: Image
Language: Textual Descriptions

UNITER [Chen et al. 2019]

VilBERT [Lu et al. NeurIPS 2019]

LXMERT [Tan and Bansal, EMNLP 2019]
Video + Language Pre-training

**Video**: Sequence of image frames  
**Language**: Subtitles/Narrations

00:00:02 --> 00:00:04  
That's why you won't go out with her again?

00:00:34 --> 00:00:36  
- Thank God you're here. Listen to this.
  - What?

00:00:66 --> 00:00:68  
(Joey:) Joey doesn't share food!
Video + Language Pre-training

- Limitations of existing methods
  - Video + Text inputs are directly concatenated, losing the temporal alignment
  - Pre-training tasks directly borrowed from Image + Text pre-training
  - Pre-training datasets limited to narrated instructional videos from Howto100M [Miech et al. ICCV 2019]

- HERO (Hierarchical EncodeR for Omni-representation learning)
  - New model architecture:
    - Local temporal alignments between frames and subtitles are captured by a Cross-modal Transformer
    - Global temporal context are modeled by a Temporal Transformer
  - New Pre-training tasks: Video-Subtitle Matching and Frame Order Modeling
  - Diverse Pre-training Datasets: Howto100M and TV dataset [Lei at al. ACL 2018]
    - We further collect two downstream datasets based on Howto100M
HERO: Hierarchical EncodeR for Omni-representation learning

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HERO: Hierarchical EncodeR for Omni-representation learning

- Temporally align subtitle sentences with frames
- Frame features: 2D ResNet Features [He et al. CVPR 2016] and 3D SlowFast Features [Feichtenhofer et al. ICCV 2019]
- Subtitle sentences are tokenized and each word are embedded following RoBERTa [Liu et al. 2019]
(Joey:) Joey doesn't share food!

That's why you won't go out with her again?

- Thank God you're here. Listen to this.
- What?

(Hero:) Hierarchical EncodeR for Omni-representation learning
Pre-training HERO

• Pre-training Tasks
  • Masked Language Modeling (MLM)
  • Masked Frame Modeling (MFM)
  • Video-Subtitle Matching (VSM)
  • Frame Order Modeling (FOM)
**Cross-Modal Transformer**

**Frame Features**

**Cross-Modal Transformer**

**Masked Language Modeling (MLM)**

Word Tokens of Subtitle $S_i$: $w_{s_i} = \{w_{s_i}^j\}_{j=1}^L$

Visual Frames aligned with $S_i$: $v_{s_i} = \{v_{s_i}^j\}_{j=1}^K$

Masking Indices: $m \in \mathbb{N}^M$

Loss Function of MLM: $L_{\text{MLM}}(\theta) = -\mathbb{E}_D \log P_{\theta}(w_{s_i}^m | w_{s_i}^\setminus m, v_{s_i})$
Masked Frame Modeling (MFM)

All subtitle sentences: \( s = \{s_i\}_{i=1}^{N_s} \)

Visual Frames: \( v = \{v_i\}_{i=1}^{N_v} \)

Masking Indices: \( m \in \mathbb{N}^M \)

Loss Function of MFM: \( \mathcal{L}_{\text{MFM}}(\theta) = \mathbb{E}_D f_\theta(v_m|v_{\backslash m}, s) \)

(1) Masked Frame Feature Regression (MFFR)
\[
f_\theta(v_m|v_{\backslash m}, s) = \sum_{i=1}^{M} \|h_\theta(v_m^{(i)}) - r(v_m^{(i)})\|_2^2
\]

(2) Masked Frame with Noise Contrastive Estimation (M-NCE)
\[
f_\theta(v_m|v_{\backslash m}, s) = \sum_{i=1}^{M} \log \text{NCE}(g_\theta(v_m^{(i)}|g_\theta(v_{\text{neg}})))
\]
Video Subtitle Matching (VSM)

VSM Flow

Frame Features

Cross-Modal Transformer

Temporal Transformer

Cosine

Query Encoder
(Sentence as Query)

Other video clips

Cross-Modal Transformer

Temporal Transformer

Cosine

VSM Frame Features

Frame Features

Word Features

Local Alignment

Global Alignment

Thank God you're here. Listen to this. What?

Query Encoder

00:00:34 --> 00:00:36

00:00:66 --> 00:00:68

(Subtitle as Query)

Cosine Similarity

Collect Frames

Frame Features

VSM Frame Features

Word Features

Other video clips

00:00:07 --> 00:00:09

That's why you won't go out with me, Joey.

00:00:34 --> 00:00:36

(Subtitle as Query)

00:00:07 --> 00:00:09

That's why you won't go out with me, Joey.

00:00:34 --> 00:00:36

(Subtitle as Query)

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(Subtitle as Question)
Video Subtitle Matching (VSM)

Start and end index of overlapping frames: $y_{st}, y_{ed}$

Loss function of local alignments: $\mathcal{L}_{local} = -\mathbb{E}_D \log(p_{st}[y_{st}]) + \log(p_{ed}[y_{ed}])$
Video Subtitle Matching (VSM)

Positive and negative video-subtitle pairs: \((s_q, v), (s_q, \hat{v}), (\hat{s}_q, v)\)
Similarity measure: \(S\)

Hinge loss: \(L_h(S_{pos}, S_{neg}) = \max(0, \delta + S_{neg} - S_{pos})\)

Loss function of global alignments:
\[
L_{global} = -E_D[L_h(S_{global}(s_q, v), S_{global}(\hat{s}_q, v)) + L_h(S_{global}(s_q, v), S_{global}(s_q, \hat{v}))]
\]
Frame Order Modeling (FOM)

Frame Features

Word Embed.

Cross-Modal Transformer

Frame Features

Word Embed.

Cross-Modal Transformer

Shared

Temporal Transformer

Loss Function of FOM:

\[ \mathcal{L}_{\text{FOM}} = -E_D \sum_{i=1}^{R} \log P[r_i, t_i] \]

Reorder Indices: \[ r = \{r_i\}_{i=1}^{R} \in \mathbb{N}^R \]

Original timestamp: \[ t = \{t_i\}_{i=1}^{R} \]

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Pre-training **HERO**

- **Pre-training Tasks**
  - Masked Language Modeling (MLM)
  - Masked Frame Modeling (MFM)
  - *Video-Subtitle Matching (VSM)*
  - *Frame Order Modeling (FOM)*

- **Pre-training Datasets**
  - TV Dataset
  - Howto100M Dataset
Our Pre-training Data for Video + Language

**TV Dataset**
- 22K video clips from 6 popular TV shows
- Each video clip is 60-90 seconds long
- Dialogue (“character name: subtitle”) is provided

**Howto100M Dataset**
- 1.22M instructional videos from YouTube
- Exclude videos in non-English languages and cut the rest into 60-second clips
- 660K video clips with English subtitles
Video + Language Downstream Tasks

**Video: Sequence of image frames**

**Language: Subtitles/Narrations**

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**Video Captioning**

Caption: Joey’s dating policy: never shares food!

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**Text-based Video Moment Retrieval**

Query: Joey’s dating policy: never shares food!

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**Video Question Answering**

Question: Why did Joey complain about his date?
Answer: She took Joey’s fries
Downstream Task 1: Video Moment Retrieval

Video Moment Retrieval = Video Retrieval + Moment Retrieval

• Subtask I: Video Retrieval
  • From video corpus, retrieve the most relevant video clip described by the query

• Subtask II: Moment Retrieval
  • Given the query, localize the correct moment from the most relevant video clip

• Evaluation:
  • Average recall at K (R@K) over all queries
  • Temporal Intersection over Union (tIOU) is used to measure the performance of moment retrieval

Query: Alex is on the phone with Izzie and he is updating her on the heart situation.

TVR [Lei et al. 2020]
Downstream Task 1: Video Moment Retrieval
Downstream Task 1: Video Moment Retrieval

Query: Joey's dating policy: never shares food!
Downstream Task 2: Video Question Answering

**TVQA** [Lei et al. EMNLP 2018]
Downstream Task 2: Video Question Answering

Q: Why did Joey complain about his date?
A: She took Joey’s fries

Q: Why did Joey complain about his date?
A: She took Joey’s fries

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A: She took Joey’s fries

Q: Why did Joey complain about his date?
A: She took Joey’s fries

Q: Why did Joey complain about his date?
A: She took Joey’s fries
Downstream Task 2: Video Question Answering
Downstream Task 2: Video Question Answering

Q: Why did Joey complain about his date?
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Q: Why did Joey complain about his date?
A: She took Joey’s fries

Q: Why did Joey complain about his date?
A: She took Joey’s fries
Text-based Video Moment Retrieval

- **Howto100M-R**
  - 67K text queries are collected for 30K 60-second video clips from Howto100M
- **Instructions:**
  - First, select a video segment
  - Then, write a caption describing the selected segment
Downstream Data Collection

Video Question Answering

• Howto100M-QA
  • QA collected for video segments annotated from video moment retrieval
  • On average, 2 questions per video segment
  • One correct answer and three wrong answers are written by the same annotator
  • Using adversarial matching [Zeller et al. CVPR 2019] to construct harder negative answers
Ablation Study

1. Best combination: MLM + MNCE + FOM + VSM
2. QA tasks benefit from FOM
3. Retrieval tasks benefit from VSM
4. Adding more data generally give better results

| Pre-training Data | Pre-training Tasks                  | TVR   | TVQA   | Howto100M-R | Howto100M-QA |
|-------------------|-------------------------------------|-------|--------|-------------|--------------|
|                   |                                     | R@1  | R@10   | R@100       | Acc.         | R@1 | R@10 | R@100 | Acc. |
| TV                | MLM                                 | 2.92 | 10.66  | 17.52       | 71.25        | 2.06 | 9.08 | 14.45 | 76.42 |
|                   | MLM + MNCE                          | 3.13 | 10.92  | 17.52       | 71.99        | 2.15 | 9.27 | 14.98 | 76.95 |
|                   | MLM + MNCE + FOM                    | 3.09 | 10.27  | 17.43       | 72.54        | 2.36 | 9.85 | 15.97 | 77.12 |
|                   | MLM + MNCE + FOM + VSM              | **4.44** | **14.69** | **22.82** | **72.75** | 2.78 | 10.41 | **18.77** | 77.54 |
|                   | MLM + MNCE + FOM + VSM + MFFR       | **4.44** | **14.29** | **22.37** | **72.75** | 2.73 | 10.12 | 18.05 | 77.54 |
| TV & Howto100M    | MLM + MNCE + FOM + VSM              | 4.34 | 13.97  | 21.78       | **74.24**    | **2.98** | **11.16** | 17.55 | **77.75** |
Ablation Study

• Comparison with two baseline models with/without pre-training
  
  • F-TRM
    • A flat BERT-like encoder
    • Input is a single sequence by concatenating video frames and subtitle sentences
  
  • H-TRM
    • Replacing Cross-modal Transformer with RoBERTa to encode subtitle only
    • Max-pooled subtitle sentence embeddings is added to temporally aligned frame embeddings

| Pre-training | Model | TVR | TVQA |
|--------------|-------|-----|------|
|              |       | R@1 | R@10 | R@100 | Acc.  |
| No\textsuperscript{8} | F-TRM | 1.99 | 7.76 | 13.26 | 31.80 |
|                | H-TRM | 2.97 | 10.65 | 18.68 | 70.09 |
|                | HERO  | 2.98 | 10.65 | 18.25 | 70.65 |
| Yes           | H-TRM | 3.12 | 11.08 | 18.42 | 70.03 |
|                | HERO  | 4.44 | 14.69 | 22.82 | 72.75 |

1. Without pre-training, HERO and H-TRM outperform F-TRM
   • Inherent temporal alignment between two modalities of videos is important

2. With pre-training, HERO outperforms H-TRM
   • Cross-modal interactions between visual frames and its local textual context is critical
Comparison with SOTA Models

| Method                  | TVR       | Howto100M-R | TVQA | Howto100M-QA |
|-------------------------|-----------|-------------|------|--------------|
|                         | R@1      | R@10        | R@100| Acc.         | Acc.        |
| XML (Lei et al., 2020) | 2.70     | 8.93        | 15.34|              |             |
| STAGE (Lei et al., 2019)| -        | -           | -    | 70.50        | -           |
| HERO w/o pre-training  | 2.98     | 10.65       | 18.42| 70.65        | 76.89       |
| HERO w/ pre-training   | **4.34** | **13.97**   | **21.78** | **74.24** | **77.75**   |

1. Compared to task-specific SOTA models, HERO outperforms with/without pre-training
2. Pre-training greatly lift HERO’s performance on downstream tasks
3. HERO achieves state-of-the-art results on all four downstream tasks
Thank You