ABSTRACT
In this technical report, we briefly introduce the solutions of our team 'PKU-WICT-MIPL' for the PIC Makeup Temporal Video Grounding (MTVG) Challenge in ACM-MM 2022. Given an untrimmed makeup video and a step query, the MTVG aims to localize a temporal moment of the target makeup step in the video. To tackle this task, we propose a phrase relationship mining framework to exploit the temporal localization relationship relevant to the fine-grained phrase and the whole sentence. Besides, we propose to constrain the localization results of different step sentence queries to not overlap with each other through a dynamic programming algorithm. The experimental results demonstrate the effectiveness of our method. Our final submission ranked 2nd on the leaderboard, with only a 0.55% gap from the first.

CCS CONCEPTS
• Computing methodologies → Visual content-based indexing and retrieval: Activity recognition and understanding.

KEYWORDS
Temporal Sentence Grounding, Natural language query, Sentence Localisation

1 INTRODUCTION
Given an untrimmed make-up video and a step query, the Makeup Temporal Video Grounding (MTVG) [5] task aims to localize a temporal moment of the target make-up step in the video. This task requires models to align fine-grained video-text semantics and distinguish make-up steps with a subtle difference. YouMakeUp [5] dataset has two characteristics: (1) The step query is mainly composed of the actions (e.g., apply powder), the tools (e.g., with the brush), and the face regions (e.g., on the eyelids), which requires the model to understand the videos and queries in a more fine-grained way. (2) Make-up steps are done step by step, which means that the temporal localization relationship relevant to the fine-grained phrase and the whole sentence. Besides, we propose to constrain the localization results of different step sentence queries to not overlap with each other through a dynamic programming algorithm. The experimental results demonstrate the effectiveness of our method. Our final submission ranked 2nd on the leaderboard, with only a 0.55% gap from the first.

2 METHODOLOGY
We first extract the video features and build a 2D temporal feature map following MMN [6]. Then, we extract phrases in the step query, encode them separately, and interact between the sentence and phrases through a transformer encoder. Finally, each sentence and phrase feature will predict an importance weight and calculate the cosine similarity with the 2D temporal feature map to obtain the sentence and phrase score maps. The importance weights are used to fuse the phrase and sentence score maps and output the final score map. We train our network with binary cross-entropy loss and cross-modal mutual matching loss following MMN [6], and further introduce an exclusiveness loss to encourage different step query predictions to be different from each other. In addition, during inference, we design a dynamic programming algorithm to select optimal temporal proposals for all step queries in a video and ensure that they do not overlap.

2.1 2D Temporal Feature Map Encoder
We use pretrained CLIP [2] model (ViT-L/14@336px) to extract the frame features (roughly three frames of CLIP features per second). We also trim the videos by step queries and fine-tune the CLIP4Clip [1] model with the video retrieval task. We fine-tune the CLIP4Clip model initialized by the pretrained CLIP ViT-B/32 weight with learning rate equals to 0.0001 and batch size equals to 64 for 5 epochs. We found that many makeup actions can be inferred by comparing the changes of the face regions before and after makeup. Thus, to help the model better understand the structure of human face, we introduce FaRL [7] face region features. For each frame of the CLIP or CLIP4Clip features, we simply average pool the face region features and concatenate them along channel dimension as the final video inputs. Finally, we build the 2D temporal feature map $V \in \mathbb{R}^{N \times N \times D}$ following MMN [6], where $N = 128$ is the number of video clips, $D = 256$ is the feature dimension.

2.2 Phrase Extraction and Query Encoder
The step queries on YouMakeUp dataset are mainly composed of the actions (e.g. apply powder), the tools (e.g. with brush), and the face regions (e.g. on the eyelids). In order to understand makeup step queries in a more fine-grained way, we use off-the-shelf SRLBERT [3] model to extract phrases from step descriptions. SRLBERT assigns semantic rule labels to each word in the sentence, which serve as our phrases. Each phrase and the step sentence query will be encoded by CLIP [2] text encoder separately. Finally, we use a
We train our network with binary cross entropy loss $\mathcal{L}_{bc}$ and cross-modal mutual matching loss $\mathcal{L}_{mm}$ following MMN [6]. The binary cross entropy loss uses the interaction over union (IoU) between the ground-truth and the proposals to supervise the score map $S$, and the cross-modal mutual matching loss contrast the positive moment-sentence pairs with the negative ones sampled from both intra and inter videos. We further introduce the exclusiveness loss $\mathcal{L}_{exc}$ to encourage different step query predictions to be different from each other. The exclusiveness loss finds the top-2 matching scores for each proposal from all the step queries in a video, and require their product to be 0. The exclusivity loss encourages any proposal to have a high matching score with at most one step query. The total loss of our method is shown blow:

$$\mathcal{L} = \mathcal{L}_{bc} + \alpha \mathcal{L}_{mm} + \beta \mathcal{L}_{exc}$$  \hspace{1cm} (4)

2.3 Phrase Similarity Learning

Instead of only localizing the step sentence query, we also localize the phrases in a fine-grained way. We compute the cosine similarity of the sentence/phrase features and the 2d temporal feature map respectively and obtain the score maps, which represent the matching score between the temporal proposals and the sentence/phrase:

$$S_i = \frac{VTP^T}{\|V\|\|T^P\|}$$ \hspace{1cm} (1)

$$S_{1p} = \frac{VT_P^TP}{\|V\|\|P\|}$$ \hspace{1cm} (2)

where $S_i \in \mathbb{R}^{N \times N}$ is the sentence score map, and $S_{1p} \in \mathbb{R}^{np \times np}$ is the phrase score maps. To measure the importance of sentence and phrases, we use a fully connected network to predict importance weights $w^s \in \mathbb{R}$, $w^p \in \mathbb{R}^N$ with text features $T_i$, $P_i$. We use a softmax activation function to ensure that these weights sum to 1. Finally, the importance weight $w^s_i, w^p$ will be used to perform a weighted summation of the score maps $S, S_{1p}$ and output the fused score map $S$:

$$S = w^s S + \sum_{i=1}^{np} w^p_i S_{1p} \in \mathbb{R}^{N \times N}$$ \hspace{1cm} (3)

2.4 Loss

We train our network with binary cross entropy loss $\mathcal{L}_{bc}$ and cross-modal mutual matching loss $\mathcal{L}_{mm}$ following MMN [6]. The binary cross entropy loss uses the interaction over union (IoU) between the ground-truth and the proposals to supervise the score map $S$, and the cross-modal mutual matching loss contrast the positive moment-sentence pairs with the negative ones sampled from both intra and inter videos. We further introduce the exclusiveness loss $\mathcal{L}_{exc}$ to encourage different step query predictions to be different from each other. The exclusiveness loss finds the top-2 matching scores for each proposal from all the step queries in a video, and require their product to be 0. The exclusivity loss encourages any proposal to have a high matching score with at most one step query. The total loss of our method is shown blow:

$$\mathcal{L} = \mathcal{L}_{bc} + \alpha \mathcal{L}_{mm} + \beta \mathcal{L}_{exc}$$  \hspace{1cm} (4)

2.5 Inference with Dynamic Programming

As makeup steps are done step by step, the temporal moments corresponding to different steps do not overlap. During inference, we design a dynamic programming algorithm to select optimal temporal proposals for all step queries in a video and ensure that they do not overlap. Specifically, we regard the predicted scores for each proposal as the probability of choosing that proposal. Let $P(k,s,n)$ denote the probability of choosing the proposal $(s,n)$ for the $k$-th step query and $K$ denote the total number of steps. Our goal is to find a sequence of nonoverlapping proposals $(s_1,n_1), (s_2,n_2), ..., (s_K,n_K)$ that maximizes the joint probability

\begin{algorithm}
\caption{Inference with dynamic programming}
\begin{algorithmic}
\State \textbf{input}: The number of steps $K$, the number of video clips $N$, and the log probability scores $S_1, S_2, ..., S_K \in \mathbb{R} \times \mathbb{N}$
\State $f_{k,n} \leftarrow -\infty, \forall k \in \mathcal{P}((1,2,...,K)), n \in \{1,2,...,N\}$
\State // $f_{k,n}$ represents the maximum score when allocate nonoverlapping proposals whose end time belongs to the $n$-th clip to the queries in the set $\mathcal{K}$
\State $g_{k,n} \leftarrow -\infty, \forall k \in \mathcal{P}((1,2,...,K)), n \in \{1,2,...,N\}$
\State // $g$ is the maximum value in the prefix of $f$ i.e.
\State $g_{k,n} = \max_{i=1,2,...,n} f_{k,i}$
\For{$n \leftarrow 1$ to $N$} \State $f_{k,n} \leftarrow \max_{\underbrace{g_{\pi,\pi},...,g_{\pi,\pi}}}_{\mathcal{K}} $ \State // $\pi$ is the maximum score when allocate nonoverlapping proposals whose end time belongs to the $n$-th clip to the queries in the set $\mathcal{K}$
\For{$k \in \mathcal{P}((1,2,...,K))$} \State $f_{k,n} \leftarrow \max_{\underbrace{g_{\pi,\pi},...,g_{\pi,\pi}}}_{\mathcal{K}} $ \State // $\pi$ is the maximum score when allocate nonoverlapping proposals whose end time belongs to the $n$-th clip to the queries in the set $\mathcal{K}$
\EndFor
\EndFor
\State $\pi \leftarrow \mathcal{K} \implies (1,2,...,K)$
\State $n \leftarrow \arg\max_{n \in \{1,2,...,N\}} f_k,n$
\EndFor
\State \textbf{output}: The $k$-th step correspond to the video clips $[s,n]$
\State $k, s \leftarrow \mathcal{P}((1,2,...,N))$
\State $f_{k,n} = g_{k,n} + S_k,s_1$ \State // $\mathcal{P}((1,2,...,N))$ represents all the models (without DP) by averaging the predicted score map.
\State $n \leftarrow \arg\max_{n \in \{1,2,...,N\}} f_k,n$
\EndFor

\end{algorithmic}
\end{algorithm}

when the proposal $(s_i,n_i)$ is chosen for the $i$-th step query. That is:

$$\{(s_i,n_i)\} = \arg\max_{\{(s_i,n_i)\}} \Pi_i P(i,s_i,n_i)$$ \hspace{1cm} (5)

satisfy:

$$\exists \pi \in \mathcal{P}_K \text{ s.t. } s_{\pi_1} < s_{\pi_2} < ... < s_{\pi_K} \leq n_{\pi_K}$$ \hspace{1cm} (6)

where $\mathcal{P}_K$ represents the set of the permutations of $K$ elements. We use the logarithmic function to turn multiplications into additions in the joint probability calculation and use the dynamic programming algorithm in Algorithm 1 to solve the above optimization problem. Since the complexity of the algorithm is $O(2^K N^K)$, we will only execute the algorithm for those samples with $K \leq 17$

3 EXPERIMENTS

As shown in Tab. 1, we compare our model with baseline MMN [6]. We denote our model without exclusiveness loss as Ours-base, denote our model with exclusiveness loss as Ours-exc, and denote the full model with face region feature as Ours-exc-f. ‘+DP’ represents inference with our dynamic programming algorithm. ‘Ensemble’ represents ensemble the all the models (without DP) by averaging the predicted score map.

Tab. 1 shows the results on the validation set. As we can see, (1) fine-grained consideration of phrases and introduction of exclusiveness loss can improve the performance. (2) During inference, the dynamic programming algorithm ensures that the predictions do not overlap, and can improve performance by about 2%. (3) The finetuned CLIP4Clip feature has a better performance than the
| Features | Methods | IoU=0.3 | IoU=0.5 | IoU=0.7 | AVG |
|----------|---------|---------|---------|---------|-----|
| CLIP     | MMN [6] | 59.43   | 46.73   | 27.57   | 44.58 |
|          | Ours-base | 60.15   | 47.46   | 28.26   | 45.29 |
|          | +DP      | 62.07   | 49.79   | 29.68   | 47.18 |
| CLIP4Clip| Ours-base | 68.42   | 53.90   | 34.07   | 52.13 |
|          | Ours-exc | 69.59   | 53.74   | 33.12   | 52.15 |
|          | Ours-exc-f | 70.22   | 56.83   | 34.73   | 53.93 |
|          | +DP      | 70.22   | 56.83   | 34.73   | 53.93 |

Table 1: Performance of different methods on the val set.

| Methods | IoU=0.3 | IoU=0.5 | IoU=0.7 | AVG |
|---------|---------|---------|---------|-----|
| Ensemble+DP | 73.61   | 62.50   | 42.12   | 59.41 |

Table 2: Performance of our ensemble model on test set.

CLIP feature, which can improve the performance by about 6.8%.
(4) Through model ensemble, the performance can be improved by 6.4%. The test set performance of our ensemble model with dynamic programming achieves the best performance on IoU=0.3 and IoU=0.5 and the second performance on IoU=0.7 and AVG, as shown in Tab. 2.

4 QUALITATIVE RESULTS

Fig. 1 shows some qualitative results of our model on the validation set. According to our statistics, with dynamic programming only performed on videos containing no more than 17 queries, we reduced the proportion of queries that overlapped with other predictions from 49.1% to 17.7%, demonstrating the effectiveness of the dynamic programming algorithm in minimizing the overlap. In Fig. 1(a), our model successfully predicted all queries correctly. In Fig. 1(b), the video clip corresponding to the first query is split into multiple shots, which results in our model predicting only one of the shots. At the same time, the two queries refer to the same tool (i.e., with the brush) and face region (i.e., cheekbone). The only difference is the makeup action (i.e., apply contour and apply highlight), yet the two actions are visually similar. Our model fails to understand the difference between these two actions at a fine-grained level and predicts the wrong answer.

5 CONCLUSION

In our submission to the PIC Makeup Temporal Video Grounding Challenge 2022, we explore the relationship between the phrases in the query in a fine-grained way, and constrain the localization results of different steps to not overlap through a dynamic programming algorithm. Experiments show the effectiveness of our method and we win the 2nd place on the leaderboard, with only a 0.55% gap from the first.

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Figure 1: Qualitative results on the validation set.