There are two popular methods in the text-video field. One is the embedding-based method. It utilizes the embeddings of features extracted from the text and video separately but suffers from the low-accuracy because of the loss of correspondence details.

The other is the model-based method. It iterates all the text-video pairs to evaluate the distance between them without extracting explicit embeddings. So it achieves better accuracy but suffers from low efficiency.

The authors of this paper proposed a novel EDB method named CRET, which solves the conflict between efficiency and accuracy.

The overview of the CRET model is shown in the slide. We can see from the picture that the proposed CRET model encodes the video and text separately. The text encoder applies the BERT as the base model to encode features into global and local features. Here the CLS represents the global features and the others are the local features. The video encoder consists of spatial and temporal encoders(encode sampled multiple frames and frame-level encoding). The spatial encoder encodes all the features into global and local features. Then we feed the global features into the temporal encoder to get the temporal embeddings. On the other side, the local feature embeddings are projected to the same dimension as the text embeddings.

On the top left of this picture, we estimate the parameters for the distribution of the features extracted from the video frames using the global video features. Then we calculate the GEES loss according to the estimated parameters and the global text features.

As for the right part of this picture, we can see that we align text and video features using the CCM module to deal with the loss of correspondence details.

Next, we will discuss more details about the two important parts of this model—CCM module and GEES loss.

Actually, the CCM module utilises the multi-head self-attention mechanism. We align these features using the transformer in which the text and video encoders share the same weights. We first calculate the distance between the token features and the query centre. Then we regard the distance as the weight of this feature. In this way, we put more importance on the features that are close to the query centre. Afterwards, we concatenate and project the aligned features from the multi-head module, and calculate the similarity score of these aligned features from text and video modalities. These are the core concepts of the CCM module and we won't go into details about the equation.

Let us move to the GEES loss. The traditional loss function NCE requires a trade-off between the accuracy and computational burden. The author improved this loss function by first making an assumption about the frame distribution. In detail, we suppose that the frame-level features of each video follow the Multivariate Gaussian Distribution. Then simplify and approximate the NCE function under this assumption. This improvement enhances the optimization efficiency of the SGD algorithm during the training process.

In a word, we improve the efficiency of the EDB method using the optimized GEES loss and enhance the accuracy by aligning the features from the text and video modalities using the CCM module.