A Implementation details

A.1 Pre-training

**Image tokenizer.** As discussed in the main paper, we adopt the Masked Patch Feature Classification (MPFC) as one of our pre-training tasks. An image tokenizer is used to convert the raw pixel values into discrete labels. While previous works like BEiT [1] applied the off-the-shelf image tokenizer pre-trained on the large-scale generic image data [12], we train the image tokenizer by ourselves on the four available fashion datasets [13,19,17,7] as focusing more on the fashion domain.

Specifically, we implement a vector-quantized VAE (VQVAE) [16] with similar Encoder and Decoder architectures as VQGAN [4]. The model details are listed in Table 1. We apply the perceptual loss [8] to learn the codebook, but disregard the adversarial loss which was used in VQGAN [4] as it has been shown to be trivial for the representation learning [3]. We adopt the same training objective as PeCo [3] to learn our VQVAE with the hyper-parameters listed in Table 2. Some reconstruction samples can be found in Fig. 1.

**Pre-training.** FashionViL is end-to-end pre-trained on 6 tasks as mentioned in the main paper. Previous fashion V+L works, i.e. FashionBERT [5] and KaleidoBERT [20], perform all the pre-training tasks in one iteration, which is memory demanding. In this work, we follow UNITER [2] to sample one task per iteration and train it with one objective.

We implement FashionViL pre-training with MMF [15] on 4 RTX 3090 GPUs. All hyper-parameters are listed in Table 3.
**Table 1. High-level architecture of the encoder and decoder of our VQVAE**

**Encoder**

\[
x \in \mathbb{R}^{224 \times 224 \times 3}
\]

Conv2D \(\rightarrow\) \(\mathbb{R}^{224 \times 224 \times 128}\)

6\(\times\) \{Res Block, Res Block, Downsample Block\} \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 512}\)

2\(\times\) \{Non-local Block, Res Block\} \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 512}\)

GroupNorm, Swish, Conv2D \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 256}\)

**Decoder**

\[
z_q \in \mathbb{R}^{7 \times 7 \times 256}
\]

Conv2D \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 512}\)

2\(\times\) \{Res Block, Non-local Block\} \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 512}\)

6\(\times\) \{Res Block, Res Block, Upsample Block\} \(\rightarrow\) \(\mathbb{R}^{7 \times 7 \times 128}\)

GroupNorm, Swish, Conv2D \(\rightarrow\) \(\mathbb{R}^{224 \times 224 \times 3}\)

**Table 2. Hyper-parameters for training our VQVAE**

| Data augmentation | RandomResizedCrop | (224, 224) |
|-------------------|-------------------|------------|
| Model configuration | Codebook size | 1024 |
| | Latent feature dimension | 256 |
| | EMA decay | 0.99 |
| Training setting | Number of iterations | 500,000 |
| | Batch size | 32 |
| | Initial LR | 1.44e-4 |
| | Optimizer | Adam (0.5, 0.9) |
| Hardware | GPU | 4 \(\times\) RTX 3090 |
| | Training duration | 96h |

**Table 3. Hyper-parameters for pre-training FashionViL**

| Image encoder | ResNet50 |
|---------------|----------|
| Text/Fusion encoder | BERT-base-uncased |
| Text tokenizer | Sequence length | 75 |
| | Mask probability | 15% |
| | Whole word mask | ✓ |
| Image tokenizer | Min masked patches | 4 |
| | Max masked patches | 8 |
| | Aspect ratio of mask | (1/3, 3) |
| Data augmentation | Resize | (256, 256) |
| | RandomCrop | (224, 224) |
| | RandomHorizontalFlip | ✓ |
| Training setting | Number of iterations | 120,000 |
| | Batch size | 256 |
| | Initial LR of TE/FE | 1e-5 |
| | Initial LR of IE | 2e-4 |
| | LR schedule | Multi-step |
| | LR steps | 45,000 and 90,000 |
| | LR decrease ratio | 0.1 |
| | Warmup iterations | 15,000 |
| | Warmup factor | 0.25 |
| | Optimizer | AdamW (0.9, 0.999) |
| | Weight decay | 1e-4 |
| Hardware | GPU | 4 \(\times\) RTX 3090 |
| | Training duration | 28.5h |
A.2 Fine-tuning

**Cross-modal retrieval (ITR & TIR).** As ITR and TIR have the same objective as image-text contrastive learning (ITC), we directly fine-tune FashionViL with $L_{\text{ITC}}$ on the FashionGen dataset [13], where the learnable temperature $\tau$ is initialized as 0.625. All hyper-parameters are listed in Table 4.

**Text-guided image retrieval (TGIR).** Previous works [10, 14] found TGIR is a sensitive task (or dataset). Even a small change in the training setting can result in a quite different model performance. For a fair and stable comparison, we keep the same experimental setting for all the experiments in Table 4 in the main paper. Specifically, we removed tricks like ensemble learning and only keep the composition module implementation. For methods with lightweight text encoders (C5, C6, C7), we use CLIP embeddings [11] as the initialization of the word embeddings, which is shown to be effective in [6]. We apply batch-based classification (BBC) loss [18] for TGIR. All experiments are conducted using the hyper-parameters in Table 5.

**Category / Subcategory recognition (CR / SCR).** For CR and SCR, we directly follow the setting of KaleidoBERT [20] with the cross entropy (CE) as the loss function. All the hyper-parameters are listed in Table 6.

**Outfit complementary item retrieval (OCIR).** We follow CSA-Net [9] for the task of OCIR. We tried hard but cannot get the proposed data splits and reproduction code in CSA-Net [9]. We thus reorganize Polyvore Outfits [17] and reproduce CSA-Net by ourselves according to the paper. As a result, our results differ from the original paper, but we will release our splits and reproduction code for the convenience of future research. All the experiments implemented by us follow the same hyper-parameters listed in Table 7. Contrastive loss is applied as the training objective.
Table 5. Hyper-parameters for fine-tuning FashionViL on TGIR

| Text/Fusion encoder | ResNet50                              |
|---------------------|---------------------------------------|
| Text tokenizer      | Sequence length 75                    |
| Data augmentation   | Resize (256, 256)                     |
|                     | RandomCrop (224, 224)                 |
|                     | RandomHorizontalFlip ✓                |
| Training setting    | Number of iterations 44,960           |
|                     | Batch size 32                         |
|                     | Initial LR of FE 1e-5                 |
|                     | Initial LR of IE 2e-4                 |
|                     | LR schedule Multi-step                |
|                     | LR steps 16,860 and 28,100            |
|                     | LR decrease ratio 0.1                 |
|                     | Warmup iterations 2,810               |
|                     | Warmup factor 0.25                    |
|                     | Optimizer AdamW (0.9, 0.999)          |
|                     | Weight decay 1e-4                     |
| Hardware            | GPU 1 x RTX 3090                      |
|                     | Training duration 5.5h                |

Table 6. Hyper-parameters for fine-tuning FashionViL on (S)CR

| Text/Fusion encoder | ResNet50                              |
|---------------------|---------------------------------------|
| Text tokenizer      | Sequence length 75                    |
| Data augmentation   | Resize (256, 256)                     |
|                     | RandomCrop (224, 224)                 |
|                     | RandomHorizontalFlip ✓                |
| Training setting    | Number of iterations 37,580           |
|                     | Batch size 32                         |
|                     | Initial LR of FE 1e-5                 |
|                     | Initial LR of IE 2e-4                 |
|                     | LR schedule Multi-step                |
|                     | Optimizer AdamW (0.9, 0.999)          |
|                     | Weight decay 1e-4                     |
| Hardware            | GPU 1 x RTX 3090                      |
|                     | Training duration 2.5h                |

Table 7. Hyper-parameters for fine-tuning FashionViL on OCIR

| Text/Fusion encoder | ResNet50                              |
|---------------------|---------------------------------------|
|                     | Resize (256, 256)                     |
|                     | RandomCrop (224, 224)                 |
|                     | RandomHorizontalFlip ✓                |
| Training setting    | Number of iterations 8,000            |
|                     | Batch size 64                         |
|                     | Initial LR of IE 1e-4                 |
|                     | LR schedule Multi-step                |
|                     | LR steps 1,500 and 5,000              |
|                     | LR decrease ratio 0.1                 |
|                     | Warmup iterations 1,000               |
|                     | Warmup factor 0.25                    |
|                     | Optimizer AdamW (0.9, 0.999)          |
|                     | Weight decay 1e-4                     |
| Hardware            | GPU 1 x RTX 3090                      |
|                     | Training duration 1.5h                |
Table 8. Results of multi-image subcategory recognition on FashionGen [13]

|                  | SCR w/o pt | SCR w/ pt | M-SCR w/o pt | M-SCR w/ pt |
|------------------|------------|-----------|--------------|-------------|
|                  | 91.45      | 78.13     | 92.33        | 83.02       |
|                  | 90.84      | 72.16     | 93.39        | 84.30       |

B Additional quantitative results

B.1 Performance on multi-image subcategory recognition

Our model can be easily extended to support multi-image input by concatenating all image tokens together. However, there is no existing downstream task taking multiple images for direct comparison with published results, thus such experiments are omitted. We have now simulated a new one – multi-image subcategory recognition (M-SCR), which takes multiple images as input. Table 8 shows that our pre-training (pt) can yield even larger gain (Acc & Macro F).

More interestingly, SCR outperforms M-SCR w/o pre-training, but the comparison is reversed after pre-training, indicating (a) the fusion of multiple images and text is not trivial, and (b) our FashionViL is effective in the fusion task.

C Additional qualitative results

We provide more visualization results in this section to better understand the performance of our FashionViL in a qualitative way.

C.1 VQVAE reconstruction

We show some reconstruction results generated by our VQVAE in Figure 1. The overall quality of the reconstructed images is satisfactory with those basic semantic information (e.g., the outline and color of the object) well preserved.

C.2 Additional t-sne visualization

We provide more t-sne visualizations for FashionViL’s joint representations on the fine-grained categories in Figure 2. In each column, we visualize all t-sne embeddings belonging to the same category (e.g., TOPS) and color them according to their subcategory labels (e.g., BLOUSES and T-SHIRTS). With the help of our pre-training tasks, the multimodal representations are better clustered in the latent space at both category-level and subcategory-level, which further proved the effectiveness of our pre-training.
Fig. 1. Some reconstruction results generated by our VQVAE. Odd rows are the original images, and even rows are the reconstructed images from the previous row.

Fig. 2. T-sne of the multimodal representations from not pre-trained and pre-trained FashionViL. Different colors represent subcategories of the categories mentioned in each column header.
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