Diversity in Fashion Recommendation Using Semantic Parsing

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Problem Statement

Recommendation based on contextual similarity

Images retrieved by finding similarity between features computed over whole image.

Images retrieved by finding similarity between features computed over semantically similar parts of image.

Query Image

Relevant Item Images

Hat
Dress
Bag
Contributions

1. Our method recommends similar images based on different parts of a query image.
2. To identify different parts we use attention and weakly labeled data.
3. Instead of features from standard pre-trained neural networks, we suggest using texture-based features.
4. We evaluate our method on item recognition task, consumer-to-shop retrieval and in-shop retrieval tasks.
Related Work

- Cloth parsing,
- Clothing attribute recognition,
- Detecting fashion style, and
- Cross-domain image retrieval using Siamese network and Triplet network.
Proposed Architecture

Localization Network, ST-LSTM focuses on different clothing items present in the image at each time step.
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Multi-label classification loss

\[ \mathcal{L}_{cls} = \frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} (p^c_i - \hat{p}^c_i)^2 \quad (1) \]

where, \( N \) is training sample, \( C \) is total number of classes, \( \hat{p}_i \) is ground truth label vector of sample \( i \) and \( p_i \) is predicted label vector of sample \( i \).
Diversity loss

Diversity loss is the correlation between adjacent attention maps,

\[ \mathcal{L}_{div} = \frac{1}{K-1} \sum_{k=2}^{K} \sum_{i=1}^{H \times W} l_{k-1,i} \cdot l_{k,i} \]  

(2)

where, \( K \) is the total steps of recurrent attention, \( H \times W \) is the height and width of attention maps, \( l_k \) is the \( k^{th} \) attention map.
Localisation loss

Localization loss, $\mathcal{L}_{loc}$ from [1] is used to remove redundant locations and force localization network to look at small clothing parts.
Combined Loss

\[ \mathcal{L} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{div} + \lambda_2 \mathcal{L}_{loc} \]  \hspace{1cm} (3)

where \( \lambda_1 \) and \( \lambda_2 \) are multiplicative factors. We use 0.01 for all our experiments.
Datasets

- **Fashion144K [2]**
  - 90,000 images with multilabel annotation.
  - 128 classes.
  - Image resolution is 384×256.

- **Fashion550K [3]**
  - 66 classes.

- **DeepFashion [4]**
  - 800,000 images
  - Similarity pairs is available for consumer-to-shop and in-shop retrieval tasks
Experiments

- Model is trained on Fashion144K [2] dataset with 59 item labels, color labels were excluded.
- Consumer-to-shop and in-shop retrieval tasks are evaluated on DeepFashion [4] dataset.
### Results

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Model</td>
<td>( AP_{all} )</td>
<td>( mAP )</td>
</tr>
<tr>
<td>StyleNet [2]</td>
<td>65.6</td>
<td>48.34</td>
</tr>
<tr>
<td>Baseline [3]</td>
<td>62.23</td>
<td>49.66</td>
</tr>
<tr>
<td>Viet et al. [5]</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Inoue et al. [3]</td>
<td>NA</td>
<td>NA</td>
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<tr>
<td>Ours</td>
<td><strong>82.78</strong></td>
<td><strong>68.38</strong></td>
</tr>
</tbody>
</table>

Multi-label classification on Fashion144k [2] and Fashion550k [3]
Results

(a) In-Shop retrieval

(b) Consumer-to-shop retrieval

Retrieval results for In-shop and Consumer-to-shop retrieval tasks on DeepFashion dataset [4].
Semantically similar results for some of the query images from Fashion144k dataset [2] using our method.
Conclusion

- Using clothing parts for recommendation gives much variability in the recommendation results.
- Attention can be used to learn discriminative features from weak labels.
- Texture cues are important for learning different parts.
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Thank you

Questions?