The Fashion IQ Dataset: Retrieving Images by Combining Side Information and Relative Natural Language Feedback

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Abstract

We contribute a new dataset and a novel method for natural language based fashion image retrieval. Unlike previous fashion datasets, we provide natural language annotations to facilitate the training of interactive image retrieval systems, as well as the commonly used attribute based labels. We propose a novel approach and empirically demonstrate that combining natural language feedback with visual attribute information results in superior user feedback modeling and retrieval performance relative to using either of these modalities. We believe that our dataset can encourage further work on developing more natural and real-world applicable conversational shopping assistants. The dataset is available for download 1.

1. Introduction

Fashion is a multi-billion-dollar industry, with direct social, cultural, and economic implications in the world. Recently, computer vision has demonstrated remarkable success in many applications in this domain, including trend forecasting [1], creation of capsule wardrobes [16], interactive product retrieval [11], recommendation [28], and fashion design [31].

In this work, we address the problem of interactive image retrieval for fashion product search. High fidelity interactive image retrieval, despite decades of research and many great strides, remains a research challenge. At the crux of the challenge are two entangled elements: 1) Empowering the user with ways to express what they want, and 2) Empowering the retrieval machine with the information, capacity, and learning objective to realize high performance.

To tackle these challenges, traditional systems have relied on relevance feedback [32], allowing users to indicate which images are “similar” or “dissimilar” to the desired image. Relative attribute feedback [23, 22] allows the comparison of the desired image with candidate images based on a fixed set of attributes. While effective, this specific form of user feedback largely constrain the information that a user can convey to retrieve images more effectively. Very recent work on image retrieval has demonstrated the power of utilizing natural language to address this problem, with relative captions describing the differences between a reference image and what the user has in mind [44, 11], and dialog-based interactive retrieval as a principled and general methodology for interactively engaging the user in a conversation to resolve their intent [11].

While this recent work represents great progress, several important questions remain. In real-world fashion product catalogs, images are often associated with side information, which in the wild, varies greatly in format and information content. Nevertheless, attributes and representations extracted from this data can form a strong basis for generating stronger image captions [49, 45, 48], and more effective image retrieval [17, 4, 36, 24]. What has been previously been unavailable is a dataset that allows researchers to explore how such information interacts with and enhances state-of-the-art systems based on relative natural language feedback.

In this paper, we introduce a new dataset and a new method to explore how natural language feedback and side information can be jointly leveraged to realize more effective image retrieval systems (see Figure 1). The dataset, which we call Fashion Interactive Queries (Fashion IQ) is situated in the detail-critical fashion domain, and we investigate the incorporation of learned, interpretable represen-
Figure 1. The Fashion IQ dataset includes attribute labels as well as relative image captions, which enables building natural language feedback based interactive image retrieval systems.

tions based on attributes, trained on metadata that is only assumed to be available during training, into state-of-the-art relative captioning systems and interactive image retrieval systems.

The contributions of this paper are as follows:

- We introduce the first dataset of real-world product images that is annotated with both human natural language sentences (~60k) and attribute labels extracted from real-world product descriptions, for research on natural language based image retrieval.

- We empirically demonstrate that incorporating side information leads to more effective user feedback modeling and image retrieval, and benchmark new and existing architectures that incorporate side information for both tasks.

- We present a new framework for dialog based interactive image retrieval that leverages both reconstructed side information and relative natural language feedback to substantially improve the state-of-the-art in image retrieval performance.

2. Related Work

Fashion Datasets. Many fashion datasets have been proposed over the past few years, covering different applications such as fashionability and style prediction [35, 18], fashion image generation [31], and product search [17, 50]. Both Dual Attribute-Aware Ranking Networks (DARN) [17] and Where to Buy It (WTBI) [12] datasets were created to solve the problem of retrieving images from professional fashion image catalogs, using consumer photos as queries. The ModaNet [52] and Clothing Co-Parsing (CCP) [47] datasets provide pixel-wise annotations for fashion apparel segmentation. DeepFashion [26, 10] is a large-scale fashion dataset containing consumer-commercial image pairs, and labels such as clothing attributes, landmarks, and segmentation masks. UT Zappos 50k [50] is a dataset of shoes created to model fine-grained visual differences. Amazon has several datasets [28, 42] with product images and other metadata such as consumer reviews and co-purchase information. Unlike existing fashion datasets used for image retrieval, which focus on content-based or attribute-based product search, our proposed dataset is focused on conversational fashion image retrieval, where user feedback is provided in natural language. In a similar vein, the Multi-Modal Domain-Aware Conversations dataset [33] uses synthetic data for user feedback, while our work makes available a unique set of human-written relative descriptions for a large set of product images.

Attributes for Interactive Fashion Search. Visual attributes, including color, shape, and texture, have been successfully used to model clothing images [17, 15, 16, 1, 51, 5, 27]. Relative attributes (e.g., “more formal than these”, “shinier than these”) [29, 37] have been exploited as a richer form of feedback for interactive fashion image retrieval [22, 23, 20, 21]. In [51], a system for interactive fashion search with attribute manipulation was presented, where the user can choose to modify a query by changing the value of a specific attribute. All these methods rely on a fixed, pre-defined set of attributes, whereas our work explores the use of feedback as relative queries in natural language, allowing more flexible and more precise descriptions of the items to be searched.

Image Retrieval with Natural Language Queries. Methods that lie in the intersection of computer vision and natural language processing, including image captioning [30, 43, 46] and visual question-answering [2, 6, 39], have received much attention from the research community. Recently, several techniques have been proposed for image or video retrieval based on natural language queries [25, 3, 40]. In [44], both image and text are used as queries for retrieval, where the text specifies a desired modification to the image. In another line of work, visually-grounded dialog systems [7, 38, 9, 8] have been developed to hold a meaningful dialog with humans in natural, conversational language about visual content. Most current systems, however, are based on purely text-based questions and answers regarding a single image. In our work, we consider the setting of goal-driven dialog, where the user provides feedback in natural language, and the agent outputs retrieved images, as originally proposed in [11]. Compared to [11], we provide a 6x larger dataset of relative captions anchored in a dataset with real-world contextual information, which will be made available to the community. In addition, we show that the use of side information can improve the performance of both relative captioning and interactive image retrieval based on natural language feedback.
Learning with Side Information. Learning with privileged information, i.e., side information that is available at training time but not at test time, is a popular machine learning paradigm [41], with many applications in computer vision [34, 17]. In the context of fashion, [17] showed that visual attributes mined from online shopping stores serve as useful privileged information for cross-domain image retrieval. Text surrounding fashion images has also been used as side information to discover attributes [4], learn weakly supervised clothing representations [36], and improve search based on noisy and incomplete product descriptions [24]. In our work, for the first time, we explore the use of side information to improve user feedback modeling and dialog-based image retrieval.

3. Fashion IQ Dataset

3.1. Dataset Collection

The images of fashion products that comprise our Fashion IQ dataset were originally sourced from Amazon.com. Similar to [1], we selected three categories of product items from the original Amazon Review data [28, 14], specifically: Dresses, Tops&Tees, and Shirts. For each image, we crawled Amazon.com and extracted corresponding product information, when available. To facilitate research on the benefits of using natural language for interactive image retrieval, we additionally collected natural language based user feedback, describing the differences between each target product image and a single reference product image. Note that these human-written relative descriptions are associated with real-world context, including side information derived from product descriptions and customer reviews. This unique feature of the Fashion IQ dataset allows researchers to investigate the advantages of natural language feedback in conjunction with such contextual information, which is often available in practice. The overall data collection procedure is illustrated in Figure 2. Basic statistics of the resulting Fashion IQ dataset are summarized in Table 1. In the following subsections, we provide additional details regarding how we collected fashion attribute labels and the relative captions.

Collecting attribute labels While the Amazon Review data contains product metadata information on titles and categories, this information tend to be short, generic and incomprehensive (c.f. Figure 3), and does not correlate well with the visual appearance of fashion images. Instead, we leveraged the rich textual information contained in the product website, and extracted fashion attribute labels from them. More specifically, product attributes were extracted from the product title, the product summary, and detailed product description. To define the set of product attributes, we adopted the fashion attribute vocabulary curated in DeepFashion [26], which is currently the most widely adopted benchmark for fashion attribute prediction. In total, this resulted in 1000 attribute labels, which were further grouped into five attribute types: texture, fabric, shape, part, and style. We followed a similar procedure as in [26] to extract the attribute labels: an attribute label for an image is considered as present if its associated attribute word appears at least once in the metadata. In Figure 3, we provide examples of the original side information provided in Amazon Review dataset and the corresponding attribute labels that were extracted.

Collecting relative captions The goal in supporting relative captions is to allow users to use natural language ex-
| # Images | # Images with side info | # Relative Captions |
|----------|------------------------|--------------------|
| 11452 / 3817 / 3818 | 7741 / 2561 / 2653 | 11970 / 4034 / 4048 |
| 19087 | 12955 | 20052 |

Table 1. Dataset statistics on Fashion IQ.

| Semantics | Quantity | Examples |
|-----------|----------|----------|
| Direct reference of target image | 49% | is solid white and buttons up with front pockets |
| Comparative reference | 32% | has longer sleeves and is lighter in color |
| Mixed use of direct and comparative references | 19% | has a geometric print with longer sleeves |
| Single-attribute phrase | 30.5% | is more bold |
| Compositional attribute phrases | 69.5% | black with red cherry pattern and a deep V neck line |
| Negation | 3.5% | is white colored with a graphic and no lace design |

Table 2. Analysis on the relative captions. Bold fonts highlight expressions which compare or contrast the image content between the target and the reference image.

expressions to more flexibly describe how a reference image (e.g. a current search result) differs from an image of what they are searching for, to realize more interactive and effective image retrieval. Essentially the same goal is sought in [11] (the primary difference being that we leverage both relative captions and side information), and so we adopted a similar data collection interface, and collected data using Amazon Mechanical Turk. Briefly, the users were situated in a context of an online shopping chat window, and assigned the goal of providing a natural language expression to communicate to the shopping assistant the visual features of the search target as compared to the provided search candidate. To ensure that the relative captions described the fine-grained visual differences between the reference and target image, we leveraged product title information to select similar images for annotation with relative captions. Specifically, we first computed the TF-IDF score of all words appearing in each product title, and then for each target image, we paired it with a reference image by finding the image in the database (within the same data split subset) with the maximum sum of the TF-IDF weights on each overlapping word. We randomly selected ~10,000 target images for each of the three fashion categories, and collected two sets of captions for each pair. Inconsistent captions were filtered. Figure 4 shows examples of image pairs presented to the user, and the resulting relative image captions that were collected.

3.2. Analyzing Fashion IQ

In Figure 5, we provided the distribution of the collected data. In general, all three datasets have similar distribution patterns, both on the lengths of the relative captions and the number of attribute labels for each associated image. Word clouds on frequent words for each dataset are in the Appendix. To further obtain insight on the properties of the relative captions, we conducted a semantic analysis on a subset of 200 randomly chosen relative captions. The results of the analysis are summarized in Table 2. The results showed that, there is an approximately even chance of the user choosing to referring to the target image directly, or utilizing the reference image for comparative descriptions. Further, the majority (69.5%) of the captions have rich information on the target image and consist of composite attribute phrases.

Figure 5. Distribution of sentence lengths and number of attribute labels for the Fashion IQ dataset.

4. Attribute-aware Dialog-Based Interactive Image Retrieval

We evolve the dialog-based interactive image retrieval framework of [11] to incorporate estimated fashion attributes as side information to improve upon and generalize the approach. The general framework, which we call attribute-aware dialog-based interactive image retrieval, follows a pipeline similar to that presented in [11], and is illustrated in Figure 6. Specifically, our framework consists of a (simulated or real) user interacting with a retrieval agent over multiple dialog turns. At the $t$-th dialog turn, the system presents a candidate image $x_t$ to the user; the user
then provides a feedback sentence $o_t$, describing the differences between the candidate image $x_t$ and the desired image; then, based on the user feedback and the dialog history up to turn $t$, $H_t = \{x_1, o_1, ..., x_t, o_t\}$, the dialog manager selects the next candidate image $x_{t+1}$ from the database and presents it to the user.

Using visual attributes as side information enhances both user feedback modeling through improved relative captioning, and the visual-semantic quality of the image representations utilized by the retriever, which leads to significantly improved retrieval results over [11]. Next, we introduce the attribute prediction network (AttrNet), which infers attributes for each image (Section 4.1), and describe how the AttrNet is integrated into both the user simulator (Section 4.2) and the retrieval system (Section 4.3).

### 4.1. Attribute Prediction Network

The process of crawling product information for attributes to associate with individual product images, while automated, can lead to noisy and incomplete attribute features. To alleviate this issue, we introduce an attribute prediction network to infer estimated attributes, which are then used by both the user simulator and the interactive retriever. For each image $x$ in the retrieval database, the AttrNet predicts a set of attribute features $\{\phi_a(x) \in \mathbb{R}^{D_a}\}$, where $a \in \{\text{texture, fabric, shape, part, style}\}$ is an attribute type indicator, and $D_a$ is the number of attributes within the corresponding attribute type. Specifically, the attribute prediction model is a multi-column neural network with shared lower layers, which takes the image as input, and outputs the attribute tags, as shown in Figure 7. The shared lower layers consists of a pre-trained ResNet-152 network [13] up to the penultimate layer, where the last fully connected layer is replaced by a trainable linear projection, followed by ReLU. We use $x$ to represent both the image and its vector representation $x \in \mathbb{R}^{D_x}$ for notational simplicity. The projected image embedding $x$ is then passed to two independent linear layers with ReLU applied to the hidden layer. The final outputs are rectified by the sigmoid function to generate the attribute features $\phi_a(x)$.

### 4.2. Attribute-aware User Simulator

The role of the user simulator in dialog-based interactive image retrieval is to act as a surrogate for real human users, and provides text-based feedback describing the difference between the target image and the candidate image. Since item attributes are an elemental part of many of the phrases people use to search for items, they naturally share similar semantics with and can enhance the quality of the relative feedback simulator. In this paper, we augment the image representation with the predicted attribute features as input to an encoder-decoder captioning model $F$ that generates user feedback sentences $\hat{o} = F(x_{\text{target}}, \{\phi_a(x_{\text{target}}), x_{\text{candidate}}, \{\phi_a(x_{\text{candidate}})\})$, where $\hat{o}$ is a sequence of word indices. The network structure of the encoder-decoder captioning model $F$ is illustrated in Figure 8 (Model #3). We incorporate attribute features into the relative captioner by first linearly projecting each set of predicted attribute features to match the dimension of the hidden state of the decoder RNN, and then concatenating them with the image features, as depicted. The difference
Response Encoder  At the $t$-th dialog turn, the response encoder embeds the candidate image $x_t$, the candidate image’s attribute features $\{\phi^a(x_t)\}$ and the corresponding user feedback $o_t$ into a joint visual semantic representation, $e_t = R(x_t, \{\phi^a(x_t)\}, o_t) \in \mathbb{R}^{D_e}$. First, the feedback (i.e., a sequence of word indices) $o_t$ is encoded by an LSTM into a vector $e_t^o \in \mathbb{R}^{D_e}$. Then, we consider two ways of combining the image feature and the attribute features to obtain the attribute-aware visual representation, $e_t^{++}$. The first approach is based on direct feature concatenation, followed by a linear projection to obtain a vector of length $D_e$. Alternatively, we adopted an attention mechanism (illustrated in Figure 6) similar to the one used in Section 4.2, where a joint visual representation is obtained by the weighted sum of the image feature and each of the attribute features. The attention weights were computed using the same scoring function as introduced in Section 4.2, which takes as input the sum of the projected visual feature and the feedback representation. Finally, given the attribute-aware visual representation, and the feedback representation, $e_t^q$, the joint visual semantic representation is computed as: $e_t = \sigma(e_t^{++} + e_t^q)$, where $\sigma$ is a ReLU layer.

State Tracker  The state tracker follows a similar design as in [11], which aggregates the encoded response representation with the dialog history from previous turns, producing a query vector $q_t \in \mathbb{R}^{D_q}$. Specifically, the state tracker is based on a Gated Recurrent Unit (GRU). The forward dynamics of the state tracker are: $h_t = GRU(e_t, h_{t-1}), q_t = W^q h_t$, where $h_t \in \mathbb{R}^{D_h}$ and $W^q \in \mathbb{R}^{D_q \times D_h}$ is a trainable matrix.

Candidate Generator  The candidate generator searches for a new candidate image, given the aggregated query vector $q_t$. We represent each candidate image in the retrieval database using the concatenation based attribute-aware visual representation, i.e., $d(x) = W^q [x, \{\phi^a(x)\}] \in \mathbb{R}^{D_h}$. We then used the L2 distance between each database feature $d(x)$ and the query vector $q_t$ to select the candidate image. Given the trainable parameters of the three components, the response encoder, state tracker and candidate generator, we optimized the entire network end-to-end, using the same policy learning procedure as proposed in [11].

5. Experiments  We first investigate the performance of our attribute prediction network (Section 5.1), and then demonstrate the empirical advantage of our attribute-aware user simulator (Section 5.2) and dialog-based interactive image retriever (5.3), which leverage these predictions, over their image-only counterparts. Finally in section 5.4, we present results demonstrating the performance advantage of our attribute-aware single-turn system over existing state-of-the-art single-turn retrieval systems. All experiments were performed on our three datasets (Dresses, Shirts and Tops&Tees), with the data split as given in Table 1.

| Attribute | Dresses | Shirts | Tops&Tees |
|-----------|---------|--------|-----------|
| Texture   | 0.50    | 0.60   | 0.78      |
| Fabric    | 0.45    | 0.53   | 0.70      |
| Shape     | 0.36    | 0.47   | 0.69      |
| Part      | 0.31    | 0.44   | 0.51      |
| Style     | 0.19    | 0.28   | 0.36      |

Table 3. Attribute prediction results on top-3 and top-5 recall scores for the five attribute types.
Table 4. Comparison on image-only, attribute-aware, and attribute-aware attentional user simulator models on common image captioning metrics. D / S / T indicate Dresses / Shirts / Tops&Tees datasets. The highest scores per dataset are highlighted. “- Image” means the image component is removed and “- Drop Attribute” shows the minimum performance when removing one of the five attribute types.

|                | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | Meteor | Rouge-L | CIDEr | SPICE |
|----------------|--------|--------|--------|--------|--------|---------|-------|-------|
| Attribute-aware (D) | 61.3   | 44.1   | 29.0   | 19.7   | 26.2   | 55.5    | 59.4  | 34.7  |
| with Attention (S)  | 57.7   | 46.3   | 32.9   | 22.3   | 27.9   | 57.1    | 78.8  | 36.6  |
| (T)               | 58.4   | 44.1   | 29.6   | 26.3   | 26.5   | 54.1    | 63.3  | 35.3  |
| - Drop Attribute (D) | 60.3   | 43.5   | 28.8   | 19.0   | 25.9   | 54.7    | 58.5  | 33.8  |
| (S)               | 56.0   | 45.4   | 31.6   | 19.8   | 25.9   | 54.7    | 58.5  | 33.8  |
| (T)               | 57.3   | 43.2   | 28.9   | 19.7   | 26.2   | 53.6    | 62.4  | 34.7  |
| - Image (D)        | 56.6   | 39.9   | 24.0   | 14.5   | 22.8   | 51.2    | 32.8  | 29.4  |
| (S)               | 48.2   | 39.1   | 24.8   | 16.1   | 23.8   | 51.7    | 50.3  | 31.7  |
| (T)               | 44.1   | 35.5   | 21.4   | 13.1   | 21.9   | 50.1    | 33.7  | 29.6  |
| Attribute-aware (D) | 58.5   | 42.0   | 26.7   | 17.5   | 24.0   | 53.2    | 42.7  | 30.8  |
| via Concatenation (S) | 54.5   | 42.6   | 29.1   | 19.4   | 25.8   | 53.5    | 47.1  | 31.8  |
| (T)               | 55.9   | 41.0   | 26.0   | 17.0   | 25.4   | 51.5    | 40.7  | 31.1  |
| Image-Only (D)     | 58.1   | 41.0   | 26.3   | 17.4   | 24.8   | 53.6    | 48.9  | 32.1  |
| (S)               | 53.2   | 41.9   | 29.0   | 19.6   | 25.9   | 53.8    | 52.6  | 32.0  |
| (T)               | 54.0   | 39.4   | 24.6   | 15.7   | 24.3   | 50.5    | 41.1  | 30.6  |

Table 4. Comparison on image-only, attribute-aware, and attribute-aware attentional user simulator models on common image captioning metrics. D / S / T indicate Dresses / Shirts / Tops&Tees datasets. The highest scores per dataset are highlighted. “- Image” means the image component is removed and “- Drop Attribute” shows the minimum performance when removing one of the five attribute types.

used Adam for all experiments with a learning rate schedule that is auto-tuned based on validation set performance. The network configurations and parameter settings are in the Appendix.

5.1. Attribute Prediction

The performance of the attribute prediction network is summarized in Table 3, with the Shirts dataset yielding the highest performance. Among the five attribute types, the Style consists of the largest set of attribute words (230) and also produces the lowest recall score among all attribute types.

5.2. User Simulator / Relative Captioning

We empirically evaluate the effect of augmenting the image representation with attribute features on the user simulator by comparing to a baseline with access to only images (Figure 8, network #1). To assess the efficacy of the attention mechanism in combining image and attribute features, we also compared to a user simulator that utilizes the attribute features by simply concatenating them to the image features (Figure 8, network #2).

Results The performance of each method is summarized in Table 4. Both the attribute-aware methods (via either attention or concatenation) outperform the image-only baseline across all metrics, suggesting that attribute prediction improves relative captioning performance. The attention-enabled attribute-aware captioner, moreover, scores significantly higher than the concatenation-based model, suggesting that the attention mechanism is better able to utilize the attribute prediction information. To assess the relative importance of the image and attribute components, we investigated removing each of the components from the inputs of attribute-aware attention model. The performance degeneration of removing the image component is more significant than removing any attribute component, indicating that the image component still plays the most prominent role in the relative captioning systems.

5.3. Interactive Image Retrieval

In this section, we investigate the empirical advantage of incorporating the estimated attribute features into dialog-based interactive image retrieval. We compare the proposed attribute-aware attention-enabled model with two baseline approaches: 1) removing the attention mechanism: concatenation of attribute and image features (attribute-aware model); (2) image-only baseline [11].

Results The image retrieval performance is quantified by the average rank percentile of the image returned by the dialog manager on the test set (P) and the recall of the target image at top-N (R@N) in Table 5. Both the attribute-aware methods (via either attention or concatenation) outperform the image-only baseline, especially on R@N, demonstrating the benefit of leveraging side information and relative feedback jointly for interactive image retrieval. Additionally, the attention-enabled model produced better retrieval results overall, suggesting that more advanced techniques for composing side information, relative feedback and image features could lead to further performance gains.

5.4. Composing text and image features for retrieval

In this section, we provide empirical studies comparing different combinations of query modalities for retrieval,
Table 5. Dialog-based interactive image retrieval performance on ranking percentile (P) and recall at N (R@N) at the 1st, 3rd and 5th dialog turns. D / S / T indicate the Dresses / Shirts / Tops&Tees datasets. The highest scores per dataset are highlighted.

| Attribute-aware (D) | R@5  | R@10 | R@50 | P | R@5  | R@10 | R@50 | P | R@5  | R@10 | R@50 |
|---------------------|------|------|------|---|------|------|------|---|------|------|------|
| with Attention (S)  | 90.52| 4.74 | 7.73 | 23.94 | 98.09| 26.45 | 36.19 | 67.72 | 98.92| 40.71 | 52.43 | 79.91 |
| (T)                 | 90.37| 3.07 | 5.16 | 17.27 | 98.02| 18.95 | 27.33 | 55.49 | 98.87| 29.49 | 40.07 | 69.71 |
| via Concatenation (S)| 90.39| 4.52 | 7.48 | 24.14 | 98.00| 26.65 | 30.18 | 59.06 | 99.03| 36.97 | 47.87 | 77.30 |
| (T)                 | 90.34| 3.22 | 5.39 | 17.75 | 98.04| 20.78 | 29.02 | 59.57 | 99.07| 35.37 | 46.41 | 76.58 |

| Image-Only (D)      | 89.45| 3.79 | 6.25 | 20.26 | 97.49| 19.36 | 26.95 | 57.78 | 98.56| 28.32 | 39.12 | 72.21 |
| (S)                 | 89.39| 2.29 | 3.86 | 13.95 | 97.40| 14.70 | 21.78 | 47.92 | 98.48| 23.99 | 32.94 | 62.03 |
| (T)                 | 87.89| 1.78 | 3.03 | 12.34 | 96.82| 10.76 | 17.30 | 42.87 | 98.30| 20.57 | 29.59 | 60.82 |

Table 6. Results on composing text and image features for image retrieval.

| Side information features | R@10 (R@50) |
|---------------------------|-------------|
| A Full model: side information, gating on text features. | 11.24 (32.39) 13.73 (37.03) 13.52 (34.73) |
| B A without side information features. | 11.49 (29.99) 13.68 (35.61) 11.36 (30.67) |
| C Image and text concatenation, linear projection [11]. | 10.52 (28.98) 13.44 (34.60) 11.36 (30.42) |

| Variants of gating connection | R@10 (R@50) |
|-------------------------------|-------------|
| D A without gating connection. | 10.42 (27.99) 12.33 (33.94) 11.48 (30.35) |
| E Gating on image features (with image feature embedding). | 9.73 (25.64) 11.62 (30.75) 10.09 (27.21) |
| F TIRG [44] (E without image feature embedding). | 8.10 (23.27) 11.06 (28.08) 7.71 (23.44) |

| Single-modality retrieval | R@10 (R@50) |
|---------------------------|-------------|
| G Relative feedback only. | 6.94 (23.00) 9.24 (27.54) 10.02 (26.46) |
| H Image feature only. | 4.20 (13.29) 4.51 (14.47) 4.13 (14.30) |
| I Side information feature only. | 2.57 (11.02) 4.66 (14.96) 4.77 (13.76) |

6. Conclusions

We introduced a novel dataset to explore how relative feedback in natural language and side information can be jointly leveraged to improve fashion product search. In addition, we proposed a novel approach that uses visual attributes mined from product descriptions to significantly improve user feedback modeling and interactive image retrieval based on natural language.

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Appendix

A. Dataset Analysis

Figure 10 shows the word clouds of the frequent words of the relative captions for each dataset. The natural language based data annotation process is able to discover a fairly rich set of fashion vocabularies. In Figure 9, we showed more examples of the collected relative captions and attribute labels in the Fashion IQ dataset. It can be seen that, often, the prominent visual differences are implicitly agreed upon by both annotators and expressed in semantically related descriptions. Additionally, in most cases, the attribute labels complement with the relative captions, while covering a different set of vocabularies.

B. Experimental Settings

Attribute Prediction Network The image embedding size \(D_x\) is 1024 in the attribute prediction network. For each attribute-specific column, the penultimate layer size for each attribute group is twice the number of attribute labels for that group (i.e., \(2 \times D_a\)). In training, we used binary cross entropy loss and Adam with an initial learning rate of 0.001.

Attribute-aware User Simulator The word embedding dimension and the decoder LSTM configuration are the same for all methods. Specifically, the word embedding size is 512-D, the decoder LSTM hidden state is 512-D and the input dimension is 1024-D. For the image-only and the attribute-aware concatenation captioning models, the image embedding is 1024-D. The attribute-aware concatenation captioning model linearly projects the concatenated attribute and image features to 1024-D. For attribute-aware attention captioning model, the image embedding is 512-D, and the projected attribute vectors are also 512-D. After concatenated with the word embedding, the input to the decoder LSTM is thus 1024-D, which is consistent with the other two models.

Image Retrieval Experiments All dialog-based interactive image retrieval methods share the same model configuration. The response encoding \(D_e\) is 512-D. The state tracker GUR hidden state \(D_h\) is 256-D. The query embedding \(D_q\) is 512-D. For composing text and image features for retrieval, the network embedding is 1024-D, which we found performed well for all methods.

C. Experiment Results

Figure 11 shows examples of the attribute-aware user simulator interacting with the dialog manager. In all examples, the target images reached final rankings within top 50 after 5 dialog turns. The target images ranked incrementally higher during the dialog and the candidate images were more visually similar to the target images. These examples show that the dialog manager is able to refine the candidate selection given the user feedback, exhibiting promising behavior across different clothing categories.
Figure 9. Examples of relative captions and image attributes collected in the datasets. The attribute labels are from the target images.

Figure 10. Word clouds indicating frequent words on the collected relative captions.
Figure 11. Examples of the simulator interacting with the dialog manager system. The right-most column shows the target images.