Instagammers, Fashionistas, and Me: Recurrent Fashion Recommendation with Implicit Visual Influence

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Department of Computer Science and Engineering
Texas A&M University, USA
Fashion-focused Opinion Leaders

Visual Posts

Related Topic: “10 pieces every woman should have in her wardrobe”, “OOTD” (outfit of the day)
Fashion-focused Opinion Leaders

Fashion Bloggers

yuribondgirl Love your outfit 😊❤️❤️

anniewearsit Anyone know where this top is from?
Fashion Bloggers
Many research has shown Fashion Bloggers can heavily influence users purchase decisions:

Vineyard et al. (2014) examined the relations between fashion bloggers and consumer purchase (e.g. “I buy one or more products which I have browsed on a blog”) and the results show they are strongly positively connected.

Zain et al. (2018) interviewed consumers and showed their purchase preferences are strongly influenced by fashion bloggers and their posts.
Our Goal: Utilizing Fashion Bloggers to Explore Fashion Trends for Dynamic Item Recommendation
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In this work, we aim to explore the influence of fashion bloggers towards user purchase behaviors to enhance fashion recommendation.
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Fashion Recommendation

Recommend personalized fashion items to users: Visual information plays a significant role in fashion recommendation.

Source of Fashion Visual Information?

- **User History***: Popular visual features across users as the fashion trend; — Highly personalized and noisy

- **Aesthetic dataset****: e.g. a well-known public Aesthetic Visual Analysis (AVA) dataset. It contains over 250,000 images with aesthetic ratings from 1 to 10 and we use the images rated 6-10 as aesthetic visual information for fashion recommendation; — Static

- **Fashion Bloggers**: (1) Dynamic (2) high quality visual information across time;

*He et al. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering, WebConf, 2016
** Yu et al. Aesthetic-based clothing recommendation, WebConf, 2018
Visual Influence-aware Fashion Recommendation: Challenges

1. How to extract **fashion features** from fashion blogger’s posts?

   - Varied across time
   - Varied by bloggers
2. How to learn \textbf{personal} implicit visual \textit{influence funnel} from fashion bloggers to users?
Visual Influence-aware Fashion Recommendation: Challenges

2. How to learn **personal** implicit visual influence funnel from fashion bloggers to users?

- **Implicit**: In practice, hard to get the explicit mapping from fashion bloggers to users and their purchases (e.g. from Instagram posts to Amazon purchases)

- **Personal**: Fashion bloggers have their own fashion preferences and a user’s visual preference is also personal, so users are personalized influenced;

- **Degree of Influence**: Users can be directly strong or indirectly weak influenced from fashion blogger;
3. How to model **visual temporal dynamics influence**?

- User dynamic states + dynamic influence;
Contribution

**Topic:** This is the first work to leverage influential fashion bloggers and their visual posts as a dynamic visual signal for user fashion recommendation;

**Dataset:** We provide a dataset — more than 130,000 Instagram time-aware visual posts from influential fashion bloggers, and it can be connected to Amazon item purchases by time; [LINK: http://people.tamu.edu/~zhan13679/]

**Method:** We propose a **Fashion Visual Influence-aware Recurrent Network (FIRN)** that effectively models temporal dynamics of fashion features from bloggers, and integrates with user personal preference for fashion recommendation;
Our Solution: Fashion Visual Influence-aware Recurrent Network (FIRN)

1. Extract Fashion Feature

2. Implicit Personal Visual Funnel

3. Influence Across Time
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1. Extract Fashion Feature

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3. Influence Across Time
2. Implicit Personal Visual Funnel

**Objective:** Based on the fashion features $h_k(t)$ of each blogger, build visual implicit influence funnel from fashion bloggers to users.
2. Implicit Personal Visual Funnel

**Objective:** Based on the fashion features $h_k(t)$ of each blogger, build visual implicit influence funnel from fashion bloggers to users

- **Implicit** influence — **visual signals** to connect bloggers with users;

\[
\min \sum_t \sum_u \|v(u, t) - h(u, t)\|_F
\]

**User Visual Vector**

**Influence-aware visual vector for user u**

Minimize the distance between user’s influence-aware visual style and user’s previous purchased items.
2. Implicit Personal Visual Funnel

**Objective:** Based on the fashion features $h_k(t)$ of each blogger, build visual implicit influence funnel from fashion bloggers to users

- Influence from extracted fashion features to users may be personalized by:
  - **Personal** — attention weights
  - **Degree of Influence** — visual distance

\[
\begin{align*}
  s_k(t) &= \text{sigmoid}(E_s h_k(t) + b_s) \\
  \alpha_k(u, t) &= \frac{\exp(w(u)^T s_k(t))}{\sum_{k'}(\exp(w(u)^T s_{k'}(t)))} \\
  \hat{h}(u, t) &= \sum_k \alpha_k(u, t) h_k(t)
\end{align*}
\]

- Project to a lower space
- Attention towards each blogger
- Influence-aware visual vector for user $u$
- Minimize the distance between user’s influence-aware visual style and user’s previous purchased items

User Visual Vector
Step 1: Extract fashion features for each blogger
FIRN: Overall

Step 2: Implicit personal fashion features
FIRN: Overall

Step 3: Dynamic visual influence
Experiments

• **How well** does FIRN for fashion recommendation?

• Whether our modeled fashion bloggers *implicit visual influence* is really helpful for recommendation?

**Dataset:**

• **Instagram***: Bloggers and their dynamic visual posts.

• **Amazon**: User clothing purchase history.

• **AVA dataset**: Aesthetic rated images.

* https://www.aransweatersdirect.com/blogs/blog/46644481-the-top-100-us-female-fashion-bloggers-to-follow-on-instagram


**Experimental Setup: Baselines**

<table>
<thead>
<tr>
<th>Model</th>
<th>Personalized</th>
<th>Temporally-aware</th>
<th>Visually-aware</th>
<th>Influence-aware</th>
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<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
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</table>

**Metrics:** Following with previous fashion recommendation, we use RMSE.
### Experiments: Recommendation Effectiveness

#### Baselines

<table>
<thead>
<tr>
<th></th>
<th>No time</th>
<th>Time aware</th>
<th>Visual Time &amp; Blogger</th>
<th>Δ</th>
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#### Datasets

![Graph showing time granularity (month) vs. RMSE for different datasets (FIRN-PH, FIRN-AVA, FIRN-Blogger (FIRN))](image-url)
Experiments: Recommendation Effectiveness

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Datasets

- FIRN consistently **outperforms** state-of-the-art methods in RMSE;
- Compared traditional fashion sources (user purchase history and AVA), using fashion bloggers brings **largest improvement** for fashion recommendation;
Experiments: Case Study

User 1

User 2

Good Performance

Poor Performance
Experiments: Case Study

FIRN can learn visual features from bloggers that are similar to users through the attention mechanism;
Experiments: Case Study

User 2

Blogger posts in same time

• FIRN can recommend items that reflect both fashion trends revealed by bloggers and the user’s purchase history;
Conclusions

This is the first work to leverage influential fashion bloggers and their visual posts as a dynamic visual signal for user fashion recommendation;

Dataset: We provide a time-aware aesthetic high-quality dataset — more than 130,000 Instagram time-aware visual posts by influential female fashion bloggers, and it can be connected to Amazon item purchases by time;

• Compare with AVA dataset which hires people to rate aesthetic scores, posts by fashion blogger contain large amount of users who like the aesthetic of their posts — fashion;
• The aesthetic features are time-aware by user posts. By tracking the visual features across time, we can track aesthetic changes over time;
Conclusions

This is the first work to leverage influential fashion bloggers and their visual posts as a dynamic visual signal for user fashion recommendation;

- **Dataset:** We provide a time-aware aesthetic high-quality dataset — more than 130,000 Instagram time-aware visual posts, and it can be connected to Amazon item purchases by time; [LINK: http://people.tamu.edu/~zhan13679/]

- **Fashion Bloggers:** Fashion bloggers do play a significant role to influence user purchase decisions across time;

- **FIRN:** FIRN provides a fashion influence-aware recommendation which integrates both current fashion trend and user personal preference for fashion recommendation;

- **Future work:** • Multiple sources. • Location-aware.
Thank you!

Instagrammers, Fashionistas, and Me: Recurrent Fashion Recommendation with Implicit Visual Influence

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Thank you!