CI-OCM: Counterfactual Inference towards Unbiased Outfit Compatibility Modeling

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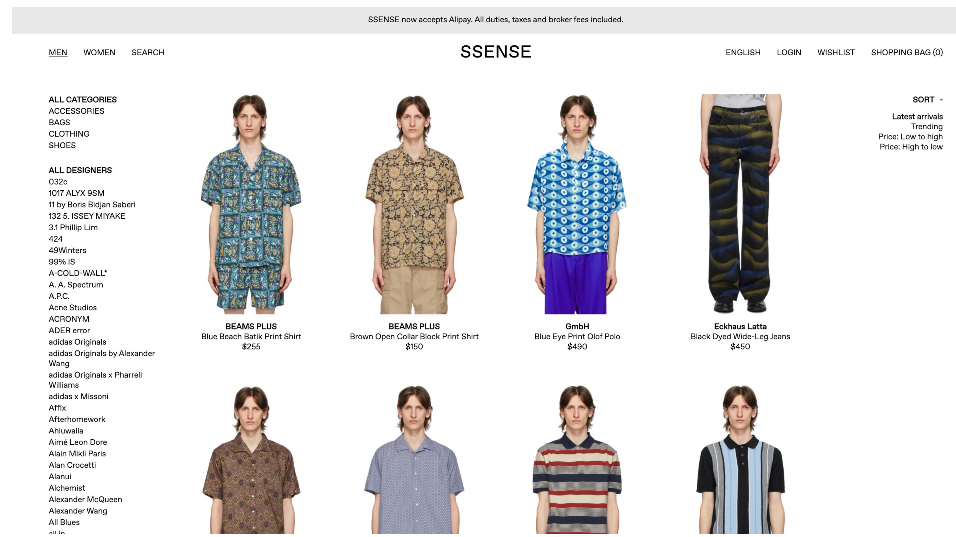
Outline

- Background
- Related Work
- Motivations
- Method
- Experiment

Background

- ➢ Huge economic value.
- ➢ Numerous online clothing data on the Internet.

The statistics and predictions of global online fashion sales.



The online clothing data, including image and category on SSENSE.

Task Definition

➢ **Outfit Compatibility Modeling**

Automatically determine whether the fashion items in an outfit are compatible.

(a) Composition 1. (b) Composition 2. (c) Composition 3.

Compatible?

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Related Work

- MSA
  - Multimodal representation learning
    - Translation-based
    - Correlation-based
    - Shared subspace learning
  - Cross-modal fusion
    - Feature-level fusion
    - Decision-level fusion

None of them consider the spurious correlations between category and matching relationship.

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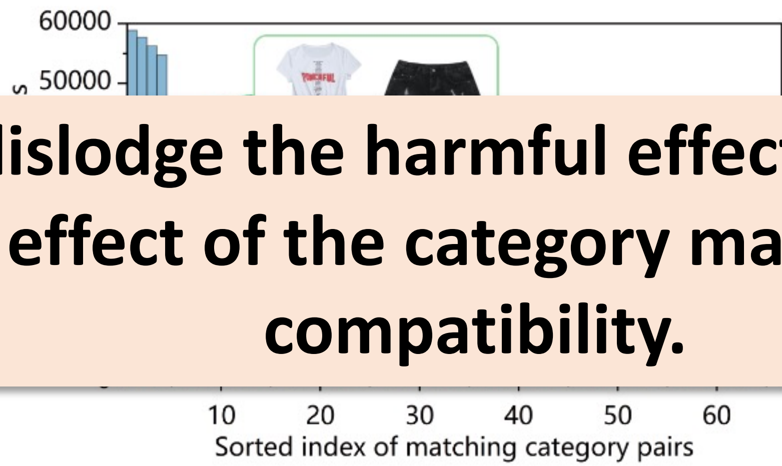
Motivations

➢ Existing studies usually suffer from fitting the spurious correlations in category matching rather than learning visual matching relationships.



How to dislodge the harmful effect and keep the beneficial effect of the category matching on outfit compatibility.

Compatible sample distribution over category matching pairs of Polyvore Outfits dataset, which are sorted according to their corresponding number of samples.

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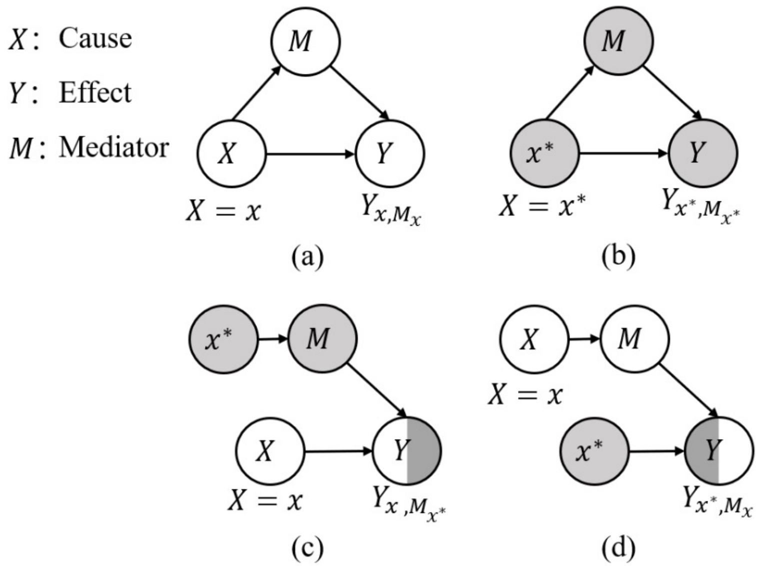
Method



Examples of Counterfactual Notations.

- Counterfactual Notions

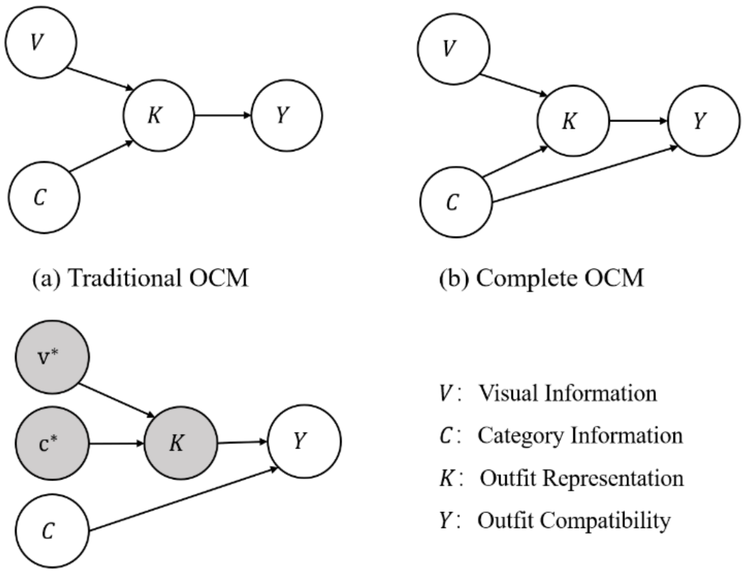
$$Y_{x,m} = Y(X = x, M = m),$$
Causal Relationship

$$TE = Y_{x,M_x} - Y_{x^*,M_{x^*}},$$
Total Effect

$$NDE = Y_{x,M_{x^*}} - Y_{x^*,M_{x^*}}.$$
Natural Direct Effect

$$TIE = TE - NDE = Y_{x,M_x} - Y_{x,M_{x^*}}.$$
Total Indirect Effect

Method



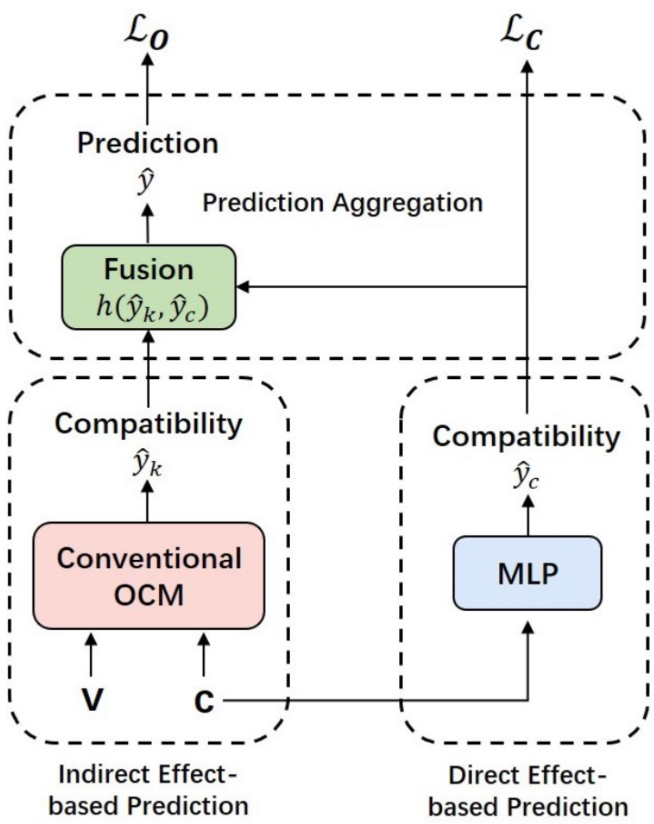
(a) Traditional OCM (b) Complete OCM (c) Counterfactual Example

Causal Relationship

$$K_{c,v} = K(C = c, V = v)$$
$$Y_k = Y_{K_{c,v}} = Y(K = K(C = c, V = v))$$

Counterfactual Notations of OCM.

Method



Framework.

Causal Relationship Implementation

$$\hat{y}_c = Y(C=c) = \mathbf{W}_3\left[\psi\left(\mathbf{W}_2\left[\psi\left(\mathbf{W}_1[\mathbf{c}_1;\cdots;\mathbf{c}_m]+\mathbf{b}_1\right)\right]+\mathbf{b}_2\right)\right]+b_3,$$

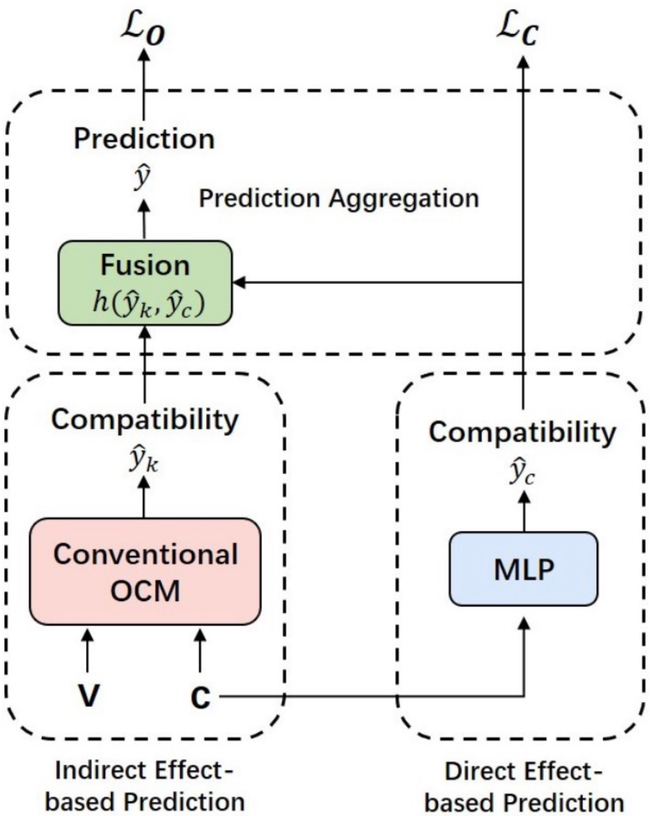
$$\hat{y}_k = Y_k = Y(K = K(C=c, V=v))$$

Training

$$\mathcal{L}_O = \sum_{(O,y)\in\mathcal{D}} -y\log(\sigma(\hat{y})) - (1-y)\log(1-\sigma(\hat{y})),$$

$$\mathcal{L}_C = \sum_{(O,y)\in\mathcal{D}} -y\log(\sigma(\hat{y}_c)) - (1-y)\log(1-\sigma(\hat{y}_c)).$$

Method



Framework.

$$NDE = Y\left(C = c, K = K_{c^*,v^*}\right) - Y\left(C = c^*, K = K_{c^*,v^*}\right),$$
$$TE = Y\left(C = c, K = K_{c,v}\right) - Y\left(C = c^*, K = K_{c^*,v^*}\right).$$

$$TE - NDE = Y\left(C = c, K = K_{c,v}\right) - Y\left(C = c, K = K_{c^*,v^*}\right).$$

$$\hat{y} = \hat{y}_k \sigma\left(\hat{y}_c\right) - \hat{y}_* \sigma\left(\hat{y}_c\right).$$

Counterfactual Inference

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Method

Experiment

Experiment

- IID Testing and OOD Testing

Notably, the split of the dataset follows the IID assumption, which is similar to most works of deep learning. Thus the deleterious effect of the long-tailed distribution on the model's generalization cannot be observed.

For this reason, we constructed an OOD dataset where distributions of matching category pairs in the testing and training sets are significantly different, to evaluate the model's generalization ability.

Experiment

➢ OOD Dataset Construction

Algorithm 1 The split of Polyvore Outfits under OOD assumption.

Input: Complete data set $\mathcal{D}$, the maximum capacity of the testing set N_t.

Output: OOD testing set $\mathcal{D}_{test}$ and remaining set $\mathcal{D}_{remain}$.

Initialize parameters: $\mathcal{D}_{test} = \emptyset$,$\mathcal{D}_{remain} = \emptyset$.

Compute the distribution of proportion P of each compatible category pair in all compatible category pairs.

Set $P' = \frac{1/P}{SUM(1/P)}$.

Get the numbers of all category pairs ϕ_{ood} in the testing set by set $\phi_{ood} = P' * N_t$.

repeat

  Randomly select an outfit O from the dataset $\mathcal{D}$.

  if O corresponds to the category matching distribution $\phi_o < \phi_{ood}$ **then**

    Set $\mathcal{D}_{test} = \mathcal{D}_{test} \cup \{O\}$, $\phi_{ood} = \phi_{ood} - \phi_o$

  else

    $\mathcal{D} = \mathcal{D} - \{O\}$

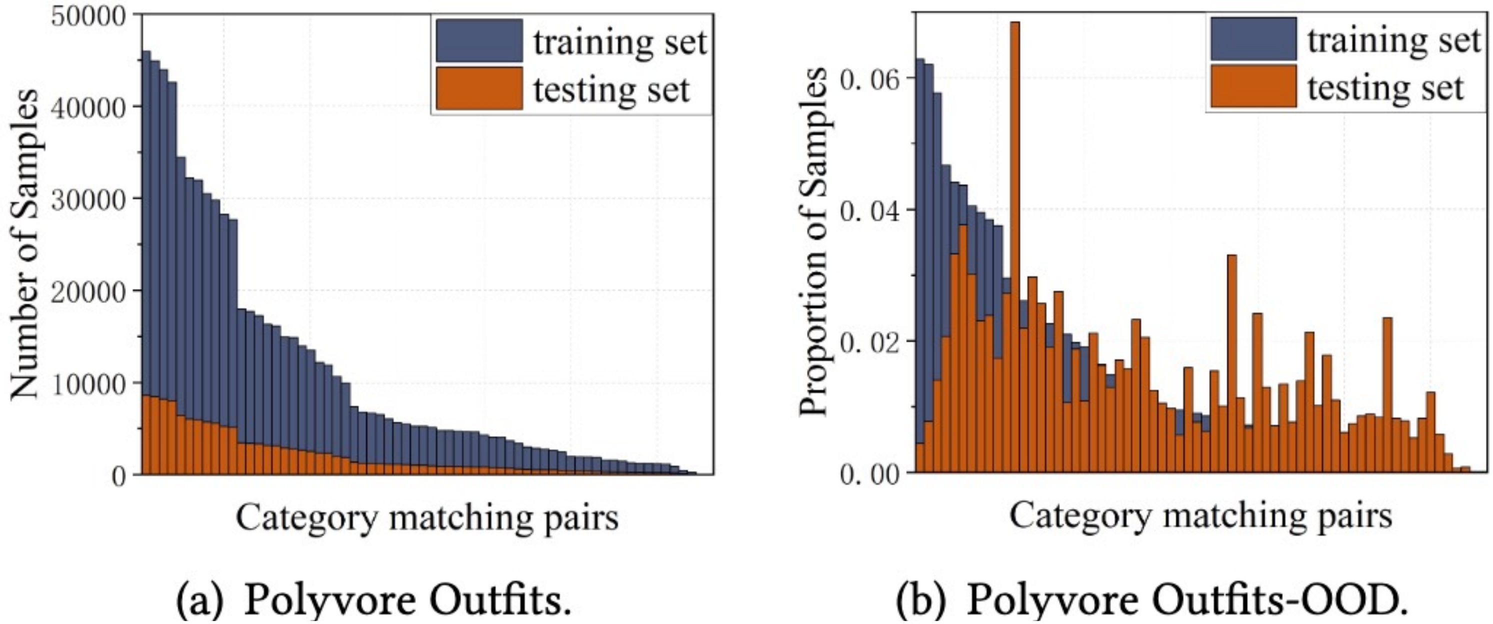
    $\mathcal{D}_{remain} = \mathcal{D}_{remain} \cup \{O\}$

  end if

until D is $\emptyset$ or $|\mathcal{D}_{test}| = N_t$.

Experiment

- OOD Dataset Construction



Distribution of category pairs for the Polyvore Outfits and Polyvore Outfits-OOD datasets.

Experiment

➢ On Model Comparison

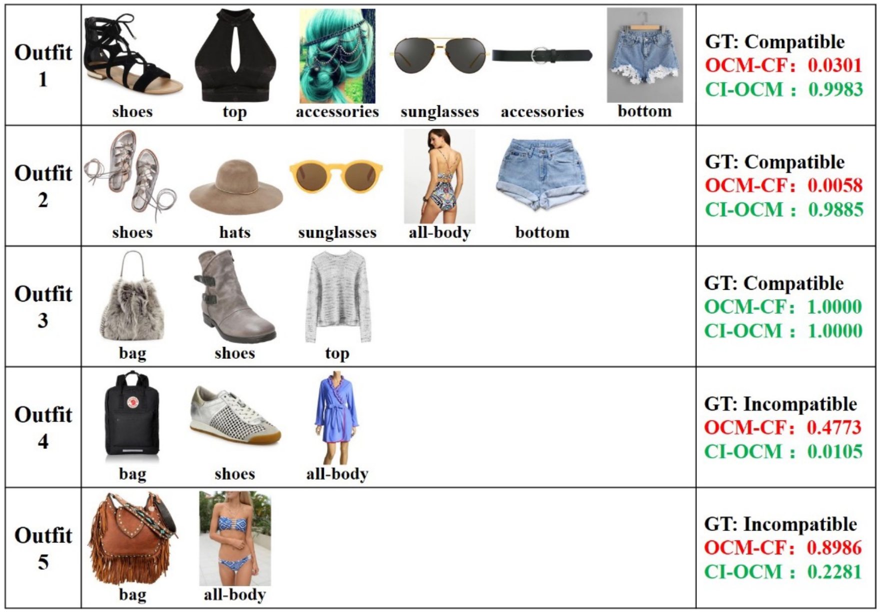
Performance comparison among different methods.

Method	Polyvore Outfits	Polyvore Outfits-OOD
Bi-LSTM	0.68	0.65
SCE-NET	0.83	0.82
Type-aware	<u>0.87</u>	0.78
NGNN	0.75	0.68
Context-aware	0.81	0.77
HFGN	0.84	0.70
OCM-CF	**0.92**	<u>0.84</u>
CI-OCM	**0.92**	**0.86**

CI-OCM consistently surpasses all the baselines, exhibiting the effectiveness of the proposed scheme.

Experiment

➢ On Case Study



Comparison between the compatibility predicted by our model and OCM-CF.

Conclusion

- We explore the **causal relationship** among variables existing in outfit compatibility modeling by the **causal graph**, pointing out the **harmful effect** hidden in the category matching.

- We present a novel **counterfactual inference** framework for outfit compatibility modeling, which **eliminates** the harmful effect and keeps the **beneficial effect** of the category matching on outfit compatibility prediction.

- We conducted **extensive experiments** on two splits of a widely-used public dataset, and the result shows the **superiority** of CI-OCM compared with existing baselines

Q&A

Thanks for your listening.

Codes are available!