Recommendation of Compatible Outfits Conditioned on Style

Debopriyo Banerjee*$, Lucky Dhakad*#, Harsh Maheshwari*#,
Muthusamy Chelliah#, Niloy Ganguly$*, and Arnab Bhattacharya#

$ - IIT Kharagpur, Kharagpur, India
*- Leibniz University of Hannover
- Flipkart Internet Pvt. Ltd., Bangalore, India.
(**CNeRG - Complex Network Research Group**)

Introduction

Outfit Recommendation

- Outfit is collection of products which go well together.

- Outfit recommendation is a relatively well studied area in which researchers aim to recommend outfits based on the notion of learning compatibility between lifestyle or fashion items [11, 17–19].

- Outfits can be categorized into different styles
  - Work
  - Casual
  - Party ….

- A substantial volume of work has been done on the specific area of personalised recommendations [13, 20].

- None of them specifically **take outfit style** into account while learning compatibility within outfits.

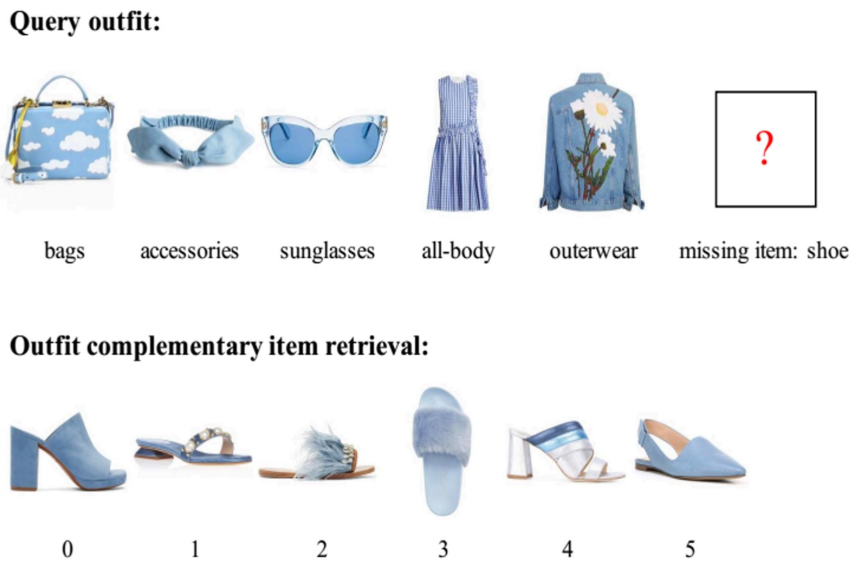
Outfit

https://depositphotos.com/39449619/stock-photo-overhead-of-essentials-hipster-woman.html

https://everydaysavvy.com/kohls-business-casual-spring-outfits/

Existing Research for Outfit Compatibility

Compatibility Model



[12] Fashion Outfit Complementary Item Retrieval

- State of art, Compatibility Models optimize outfit level loss
- The model is trained to learn missing item in partial outfit such that complete outfit is compatible with the missing item.
- Compatible loss is modelled as Fill in the blanks loss

Motivation and Objective

Style

- An outfit may look **compatible** under **one style construct**, but **not in another**.
- Outfit **compatibility** depends on **style.**

Objective - For a chosen fashion item (as an anchor), a set of desired item categories as a template and a user-defined outfit style, we aim to **complete the look** by generating top-k compatible outfit sets (each having the common anchor item and other items conforming the template).

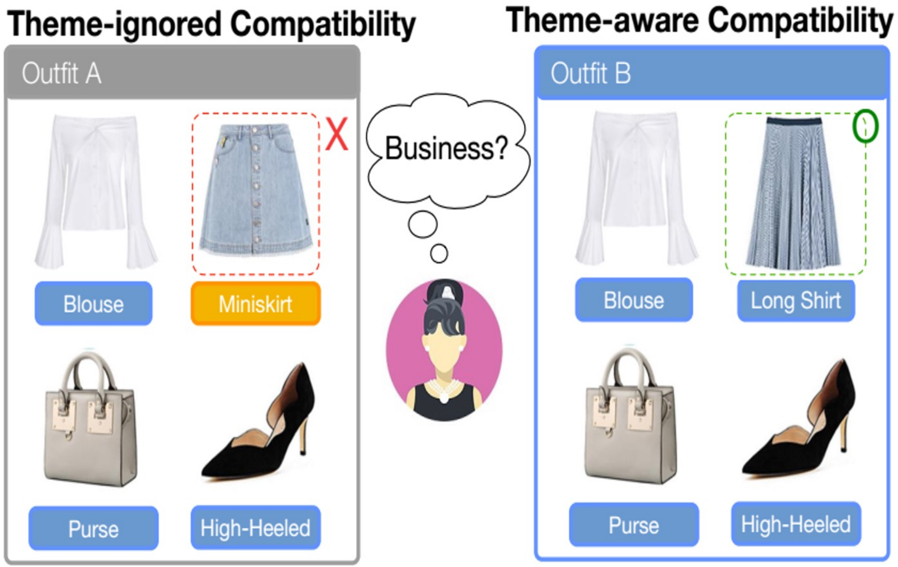
Template: < **tops**, skirts, shoes, watches >
where **tops** is the category of the anchor

	Outfit o_1 (Formal)	Outfit o_2 (Casual)
Style-Independent	$compat(o_1) = 1$	$compat(o_2) = 0$
Style-Guided	$compat(o_1 \mid style = formal) = 1$	$compat(o_2 \mid style = casual) = 1$

Illustration of the effectiveness of style-guided outfit generation over a style-independent variant.

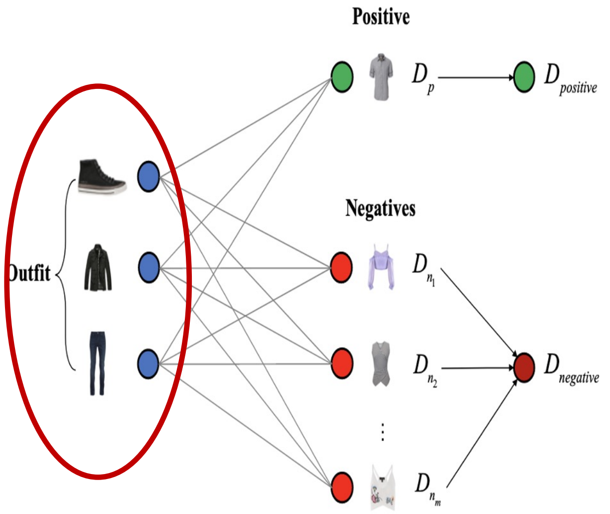
Research Direction for Style

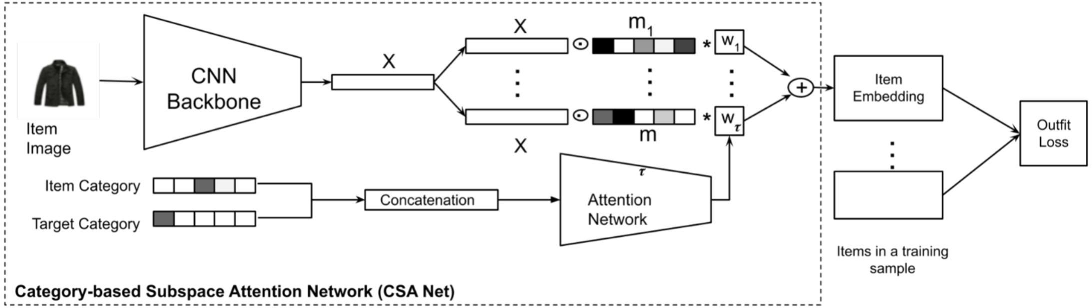
Compatibility + Style Model



- We augment **style information** to learn an improved compatibility prediction model named as SATCORec(Style-Attention-based Compatible Outfit Recommendation).
- The learned model helps in generating suitable outfits for a given anchor item and a style in the most efficient way.

Compatibility Model





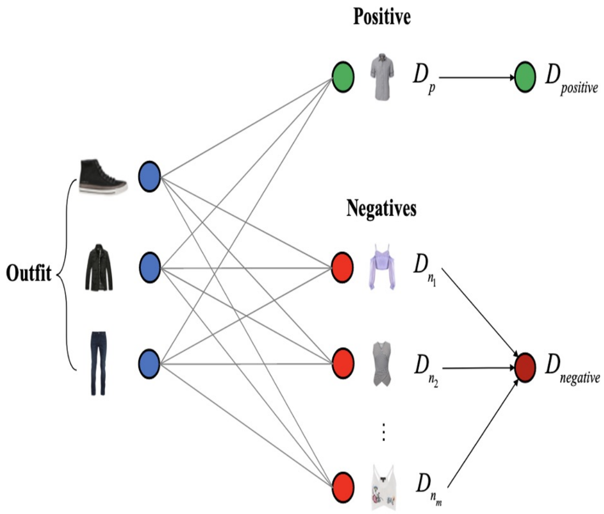
$$\mathcal{L}_{compat} = \max(0, D_p^{s_k} - D_N^{s_k} + m)$$

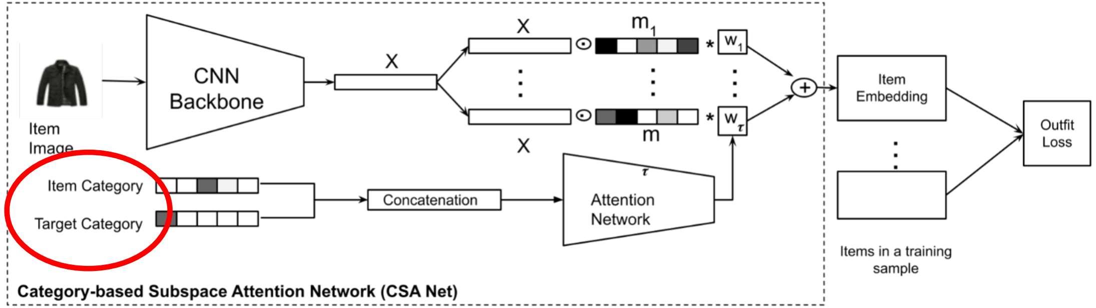
D = Distance(Item Embedding – Outfit Embedding)

Compatibility Model (State of Art)

Lin, Yen-Liang et al., Fashion Outfit Complementary Item Retrieval, CVPR'20

Compatibility Model





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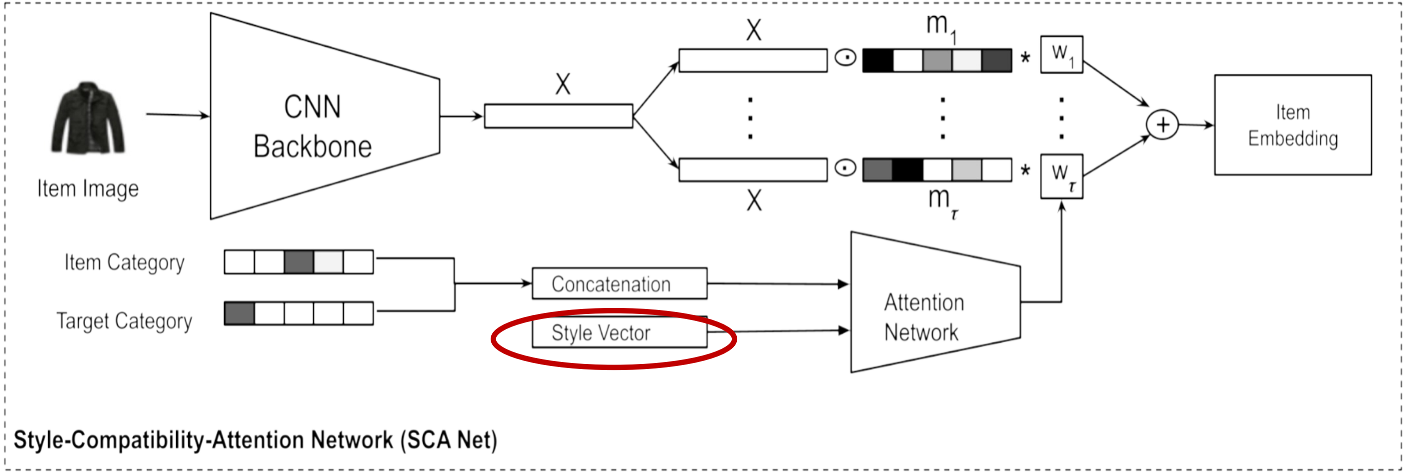
Proposed Approach

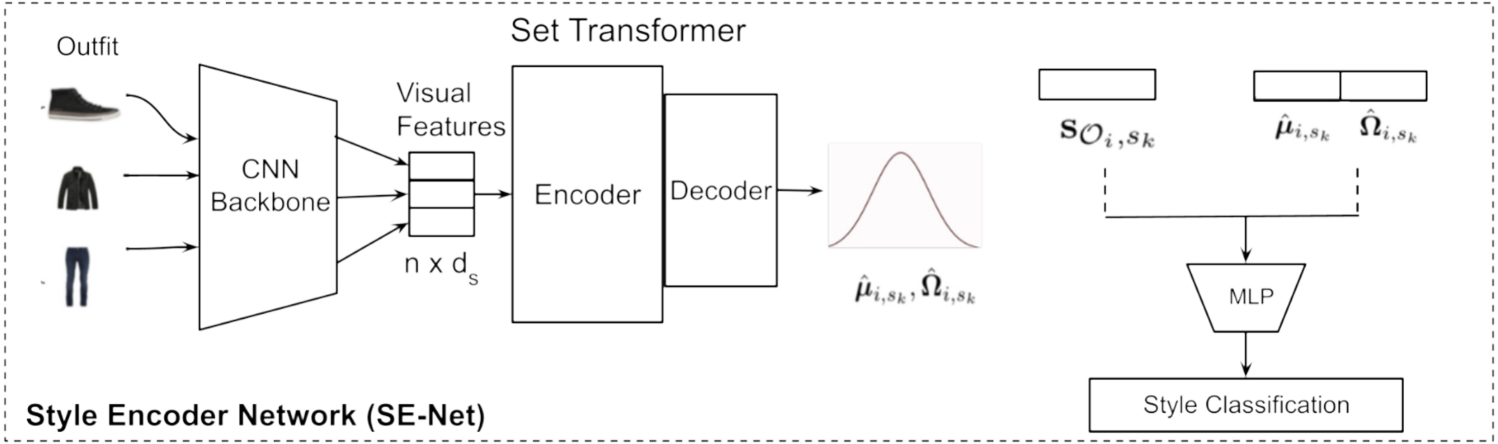


$$\mathcal{L}_{compat} = \max(0, D_p^{s_k} - D_N^{s_k} + m)$$

$$\mathcal{L}_{stylecompat} = \max(0, D_p^{s_k} - D_p^{s_q} + m)$$

SCA-net Model with style loss

Proposed Approach

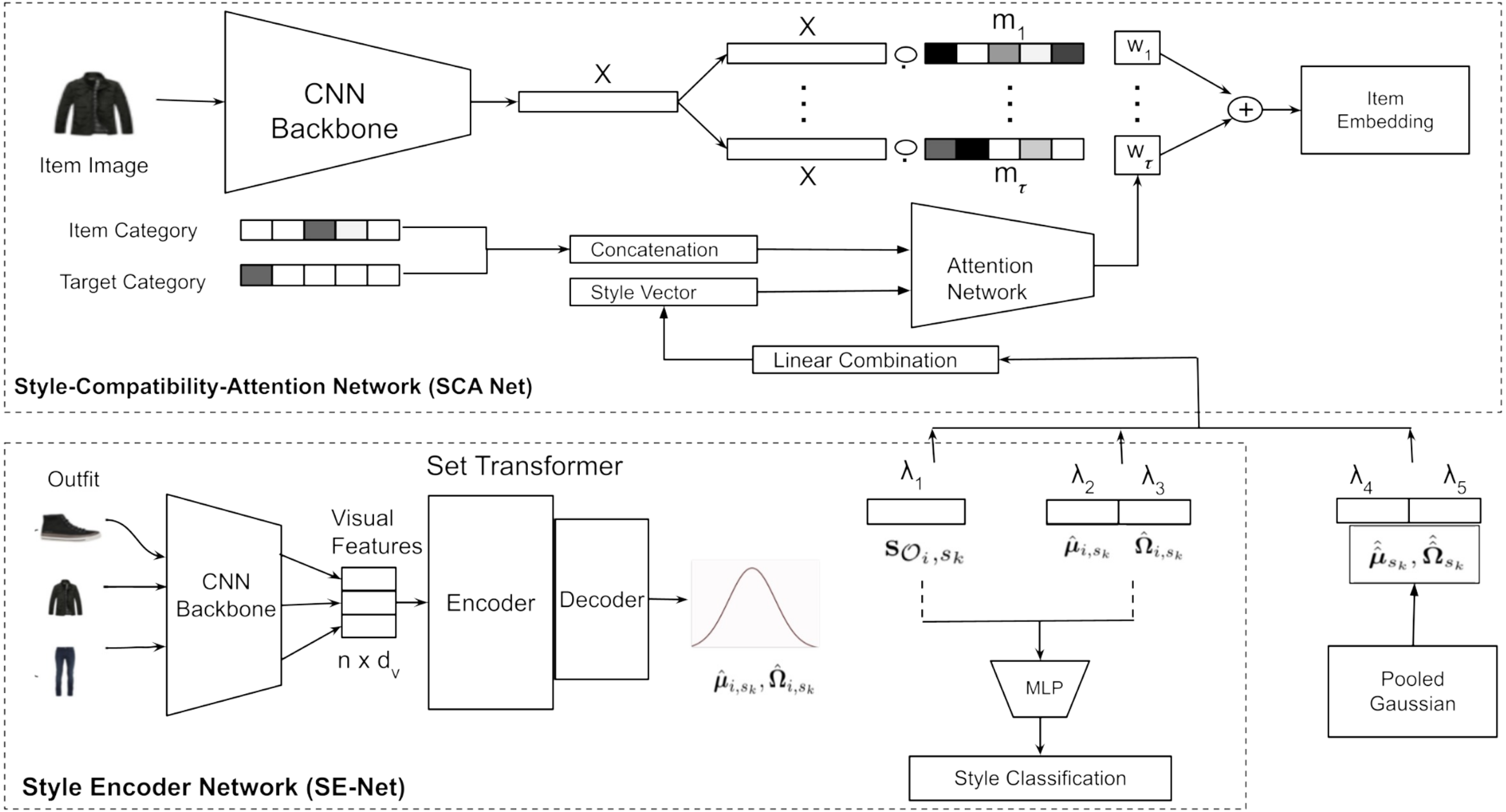


$$\mathcal{L}_{Style} = \mathrm{KL}(\mathcal{N}(\hat{\boldsymbol{\mu}}_{i,s_k}, \hat{\boldsymbol{\Omega}}_{i,s_k}) \,||\, \mathcal{N}(0, \mathbb{1}))$$

$$\mathcal{L}_{\mathrm{classif}} = -\sum_{i=1}^{m} y_{s_k} log(\hat{p}(O_i \mid s_k))$$

SE-net Model with Style Classification and KL Divergence loss

Proposed Approach



Model Loss

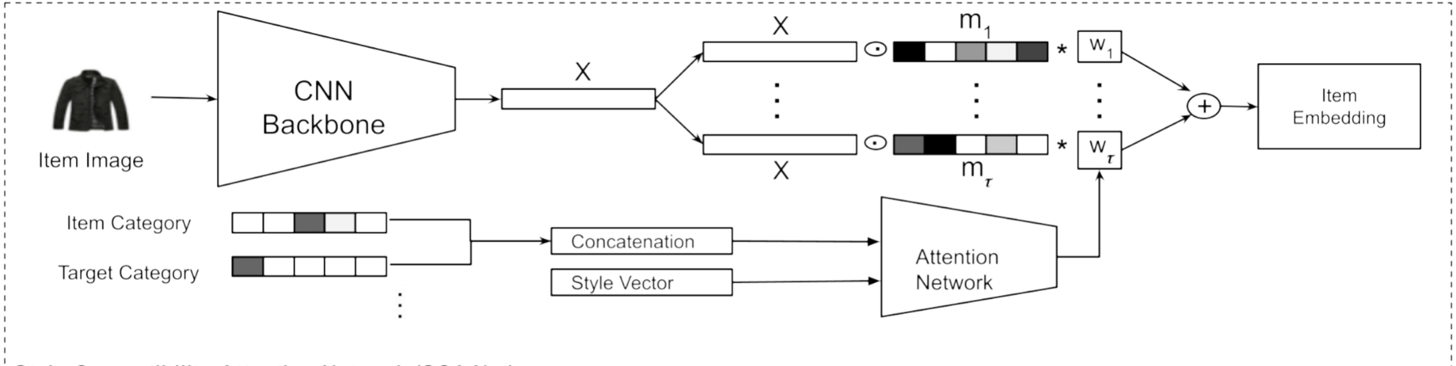
Style Vector

$$\mathbf{r}_{\mathcal{O}_i,s_k} \equiv \left[\lambda_1\,\mathbf{s}_{\mathcal{O}_i,s_k} + \lambda_2\,\hat{\boldsymbol{\mu}}_{i,s_k} + \lambda_4\,\hat{\hat{\boldsymbol{\mu}}}_{s_k},\, \lambda_3\hat{\boldsymbol{\Omega}}_{i,s_k} + \lambda_5\hat{\hat{\boldsymbol{\Omega}}}_{s_k}\right]$$

Variations	λ1	λ2	λ3	λ4	λ5	
SATCORec-r	1	0	0	0	0	Input Outfit Representation Sample
SATCORec-(p_m+g_m)	0	λ	0	1	0	Mean of outfit and Global Style Representation
SATCORec-(r+g_m)	λ	0	0	1	0	Input Outfit Representation Sample and Global Style Representation
SATCORec-p	0	1	1	0	0	Mean and variance of Input Outfit
SATCORec-(p+g)	0	λ	λ	1	1	Combination of Outfit Representation and Global Style Representation

Variations of SATCORec that have been experimented with

Outfit Generation



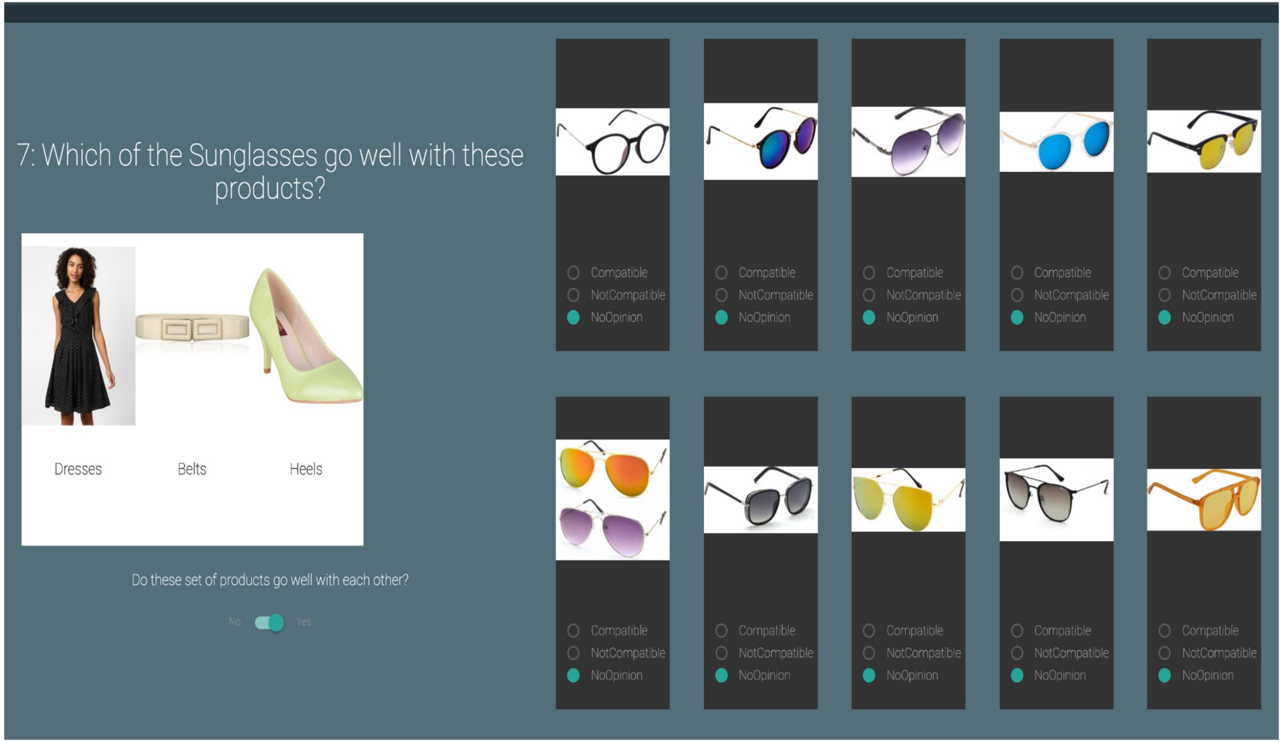
Style-Compatibility-Attention Network (SCA Net)

Beam Search using SCA-net

Example Outfits per Style

Outfits generated for same anchor item with varying styles

Data Annotation



Data Annotation Interface

- Manual Creation of Outfits for multiple styles by **Domain experts**
- Expanding outfits by extracting similar items from catalog using attribute similarity
- Using Data Annotation Interface, **Annotate similar items** as compatible or not.
- Multiple Taggers tag single sample, to get high confident data.

Dataset Statistics and Evaluation Metrics

Distribution of compatible outfits across different styles

Style	Party	Outdoor	Summer	Formal	Athleisure	Winter	Casual	Celebrity	Total
Training	8183	6280	7061	5136	16232	16028	5194	5424	69538
Validation	1174	1001	1204	840	1981	2135	791	808	9934
Testing	3018	1937	2551	1648	2506	4695	2034	1480	19869

Quantitative Results

Fill in the Blank (FITB) Accuracy									
Q:	q_1	q_2	_	q_4	A:	a_1	a_2	a_3	a_4

Compatibility AUC (Compat. AUC)									
O_p:	q_1	q_2	q_3	q_4	O_n:	q_1	x	q_3	q_4

Hard Negative (HN) Samples: Random sampling from matching fine-grained categories.
For example, replacing a shirt in a positive outfit with a random shirt.

Soft Negative (SN) Samples: Random sampling from matching high level categories.
For example, replacing a top-wear in a positive outfit with a random top-wear.

Entropy : To measure entropy, we pick anchor items which belong to outfits from multiple styles. We rank all the outfits using each baseline given a style and pick the best one. For baselines which are independent of style we get top-K outfits where K is total styles in data. This helps capture that user gets maximum utility for a product if it can be used in multiple styles.

Quantitative Results

Method	FITB		Compat. AU-ROC		Entropy
	HN	SN	HN	SN	
Theme Matters	38.53+-0.17	63.2+-0.21	85.4+-0.15	93.85+-0.1	0.61
CSA-Net	53.14+-0.17	67.05+-0.25	94.42+-0.03	96.3+-0.03	0.48
SATCORec-r	**53.32+-0.18**	66.63+-0.15	94.47+-0.02	95.99+-0.04	**1.09**
SATCORec-p	52.06+-0.10	**67.31+-0.14**	**94.78+-0.02**	**96.47+-0.02**	0.97
SATCORec-(p+g)	46.56+-0.05	61.03+-0.17	88.41+-0.02	90.10+-0.02	0.78
SATCORec-(r+g_m)	47.61+-0.12	60.70+-0.06	88.88+-0.06	91.34+-0.02	0.12
SATCORec-(p_m+g_m)	49.73+-0.05	63.02+-0.11	90.96+-0.05	92.25+-0.02	0.63

Comparison of Compatibility Learning for different methods on the Dataset

Quantitative Results

Rank : To measure rank given a style, we pick anchor items which belong to outfits from multiple styles. For style based models, we measure given the style per anchor item compatibility score per outfits and measure the rank of outfit with correct style.

Using rank, we compare the models using the following metrics

		SATCORec-r	**SATCORec-p**	**Theme Matters**
Metric	MRR of correct style	**0.8844**	0.7676	0.6213
	Correct style on 1st rank	**80.94**	59.36	42.37
	Correct style in top 3 ranks	95	**95.1**	76.51
	Avg rank of the correct style	**1.4**	1.7	2.5

Comparison of different baselines on Rank of correct styles

Quantitative Results

Anchor Topwear	Athleisure Bottomwear	Casual Bottomwear	Formal Bottomwear
			
Style Pre-conditioning	**Bottomwear 1**	**Bottomwear 2**	**Bottomwear 3**
Athleisure	1	0	0
Formal	0	0	1
Casual	0	1	0

Style Conditioned Ranking of Items

Quantitative Results

Top-1 Accuracy : For each anchor item which belong to outfits with multiple styles, we check the top-1 accuracy of selecting the right child item in the outfit conditional on the style.

	Top-1 Accuracy	**SATCORec-r**	**SATCORec-p**	**Theme Matters**
Parent-Child	Topwear - Bottomwear	66.74	**77.33**	50.32
	Bottomwear - Topwear	72.02	**86.65**	57.92
	Topwear - Footwear	65.79	**75.97**	59.73
	Bottomwear - Footwear	69.81	**80.13**	62.79

Comparison of different baselines on Accuracy of top-1 child product style

Combination of Styles

Outfits generated for same anchor item with combination of styles

Thank You
For your Attention
https://harshm121.github.io/project_pages/satco_rec.html

Any Questions?

Email: niloy@cse.iitkgp.ac.in @gangulyniloy
Complex Network Research Group (CEnRG) : @cnerg

Quantitative Results

Method	Party	Outdoor	Summer	Formal	Athleisure	Winter	Casual	Celeb	Overall
TypeAware	28.33	29.22	10.24	33.54	19.52	18.1	2.67	15.92	19.3
BPR-DAE	28.19	17.07	17.74	36.26	31.64	29.05	23.42	19.05	25.64
TransNFCM	12.78	25.72	3.09	23.84	30.01	21.21	0	27.86	18.36
CSA-Net	34.63	26.79	13.98	35.44	28.69	26.94	11	27.11	25.38
ThemeMatters	34.26	24.2	7.48	24.68	14.21	30.05	18	9.95	21.39
SATCORec-r	**50.56**	**32.12**	19.84	45.78	**38.65**	39.31	18.17	25.62	**34.27**
SATCORec-p	38.59	21.89	**23.06**	**47.26**	37.18	**40.92**	**24.09**	**28.09**	32.96

Comparison of style-specific fine-grained categories chosen by different methods.

References

[1] Elaine M. Bettaney, Stephen R. Hardwick, Odysseas Zisimopoulos, and Benjamin Paul Chamberlain. 2019. Fashion Outfit Generation for E-commerce. arXiv:1904.00741

[2] David M. Blei, Alp Kucukelbir, and Jon D. McAuliffe. 2017. Variational Inference: A Review for Statisticians. *J. Amer. Statist. Assoc.* 112, 518 (2017), 859–877.

[3] Wen Chen, Pipei Huang, Jiaming Xu, Xin Guo, Cheng Guo, Fei Sun, Chao Li, Andreas Pfadler, Huan Zhao, and Binqiang Zhao. 2019. POG: Personalized Outfit Generation for Fashion Recommendation at Alibaba IFashion. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD '19)*. Association for Computing Machinery, 2662–2670.

[4] Xintong Han, Zuxuan Wu, Yu-Gang Jiang, and Larry S. Davis. 2017. Learning Fashion Compatibility with Bidirectional LSTMs. In *Proceedings of the 25th ACM International Conference on Multimedia (MM '17)*. New York, NY, USA, 1078–1086.

[5] Youngseung Jeon, Seungwan Jin, and Kyungsik Han. 2021. FANCY: Human-Centered, Deep Learning-Based Framework for Fashion Style Analysis. In *Proceedings of the 2021 World Wide Web Conference (WWW '21)*. 2367–2378.

[6] Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In *Proceedings of the 3rd International Conference on Learning Representations (ICLR '15)*. 1–15.

References

[9] Juho Lee, Yoonho Lee, Jungtaek Kim, Adam Kosiorek, Seungjin Choi, and Yee Whye Teh. 2019. Set Transformer: A Framework for Attention-based Permutation-Invariant Neural Networks. In *Proceedings of the 36th International Conference on Machine Learning (PMLR '19, Vol. 97)*. 3744–3753.

[10] Kedan Li, Chen Liu, and David Forsyth. 2019. Coherent and Controllable Outfit Generation. *CoRR* 1906.07273 (2019), 1–9.

[11] Zhi Li, Bo Wu, Qi Liu, Likang Wu, Hongke Zhao, and Tao Mei. 2020. Learning the Compositional Visual Coherence for Complementary Recommendations. In *Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI '20)*. 3536–3543.

[12] Yen-Liang Lin, Son Tran, and Larry S. Davis. 2020. Fashion Outfit Complementary Item Retrieval. In *Proceedings of the 2020 IEEE Conference on Computer Vision and Pattern Recognition (CVPR '20)*. 3308–3316.

[13] Zhi Lu, Yang Hu, Yan Chen, and Bing Zeng. 2021. Personalized Outfit Recommendation With Learnable Anchors. In *Proceedings of the 2021 IEEE Conference on Computer Vision and Pattern Recognition (CVPR '21)*. 12722–12731.

References

[14] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton van den Hengel. 2015. Image-Based Recommendations on Styles and Substitutes. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Santiago, Chile) *(SIGIR '15)*. 43–52.

[15] Takuma Nakamura and Ryosuke Goto. 2018. Outfit Generation and Style Extraction via Bidirectional LSTM and Autoencoder. *CoRR* 1807.03133 (2018), 1–9.

[16] Anirudh Singhal, Ayush Chopra, Kumar Ayush, Utkarsh Patel, and Balaji Krishnamurthy. 2020. Towards a Unified Framework for Visual Compatibility Prediction. In *Proceedings of the 2020 IEEE Winter Conference on Applications of Computer Vision (WACV '2020)*. 3596–3605.

[17] Xuemeng Song, Liqiang Nie, Yinglong Wang, and Gary Marchionini. 2019. Compatibility Modeling: Data and Knowledge Applications for Clothing Matching. *Synthesis Lectures on Information Concepts, Retrieval, and Services* (2019).

[18] Mariya I. Vasileva, Bryan A. Plummer, Krishna Dusad, Shreya Rajpal, Ranjitha Kumar, and David Forsyth. 2018. Learning Type-Aware Embeddings for Fashion Compatibility. In *Proceedings of the 2018 European Conference on Computer Vision (ECCV '18)*. 405–421.

[19] Jianfeng Wang, Xiaochun Cheng, Ruomei Wang, and Shaohui Liu. 2021. Learning Outfit Compatibility with Graph Attention Network and Visual-Semantic Embedding. In *Proceedings of the 2021 IEEE International Conference on Multimedia*

References

[20] Huijing Zhan, Jie Lin, Kenan Emir Ak, Boxin Shi, Ling-Yu Duan, and Alex C. Kot. 2021. A3-FKG: Attentive Attribute-Aware Fashion Knowledge Graph for Outfit Preference Prediction. *IEEE Transactions on Multimedia* (2021), 1–13.

[21] Aston Zhang, Zachary C. Lipton, Mu Li, and Alexander J. Smola. 2021. Dive into Deep Learning. *CoRR* 2106.11342 (2021).