Learning More from Less: Weak Supervision and Beyond

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The battle against the long tail

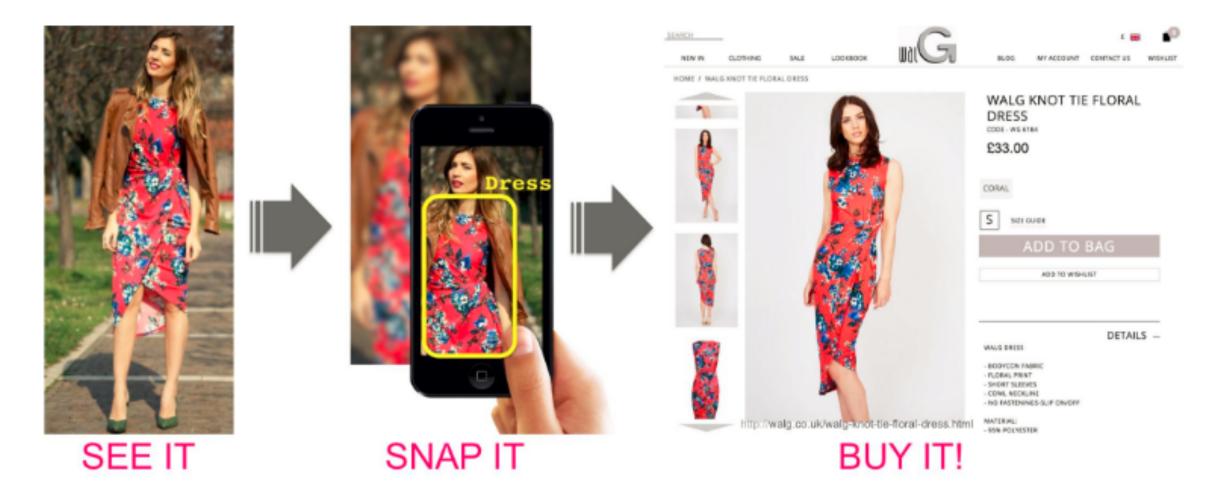
- Training accurate deep neural network models usually requires lots of labeled data
- Data collection and annotation is expensive, tedious, time-consuming.
- Crowdsourcing may be infeasible for proprietary data.
- For some tasks, data may not be available at all (long tail distribution)



Weak supervised learning for fashion search

Learning with less labels beyond weak supervision

Street2Shop



Hadi Kiapour, M., Han, X., Lazebnik, S., Berg, A. C., & Berg, T. L. Where to buy it: Matching street clothing photos in online shops. ICCV 2015

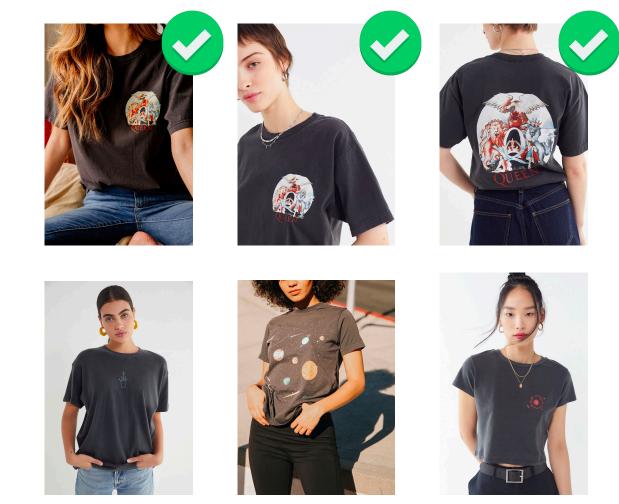
Slide credit: Tamara Berg

Street2Shop Clothing Retrieval

Input: User Photo



Retrieved Images from **Online Shopping** Stores



[Liu et al, CVPR 2012] [Kiapour et al, ICCV 2015] [Huang et al, ICCV 2015]

Problem: Domain Discrepancy





Proposed Approach: Dual Attribute-Aware Ranking Network (DARN)



DARN

Weakly labeled data from shopping websites

9,000 image pairs mined from customer review websites (exact same clothing)





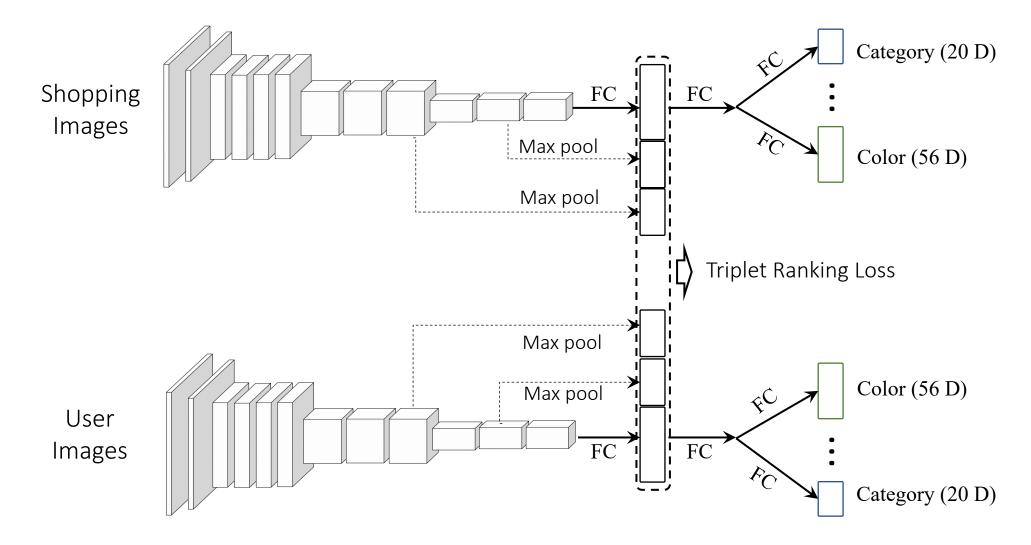


Noisy attribute labels mined from online shopping stores (9 classes, 179 values)

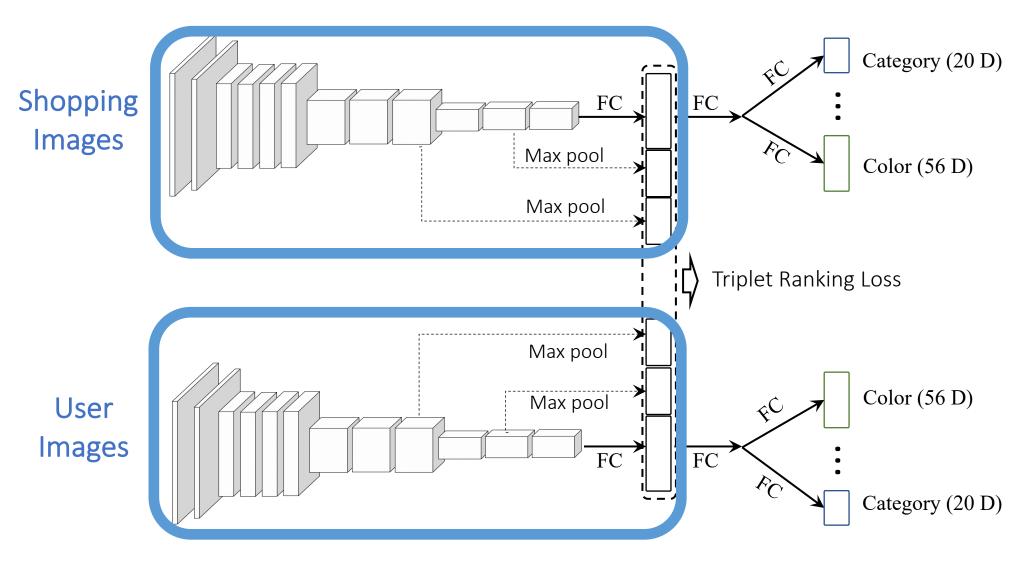


Attribute categories	Examples (total number)
Clothes Button	Double Breasted, Pullover, (12)
Clothes Category	T-shirt, Skirt, Leather Coat (20)
Clothes Color	Black, White, Red, Blue (56)
Clothes Length	Regular, Long, Short (6)
Clothes Pattern	Pure, Stripe, Lattice, Dot (27)
Clothes Shape	Slim, Straight, Cloak, Loose (10)
Collar Shape	Round, Lapel, V-Neck (25)
Sleeve Length	Long, Three-quarter, Sleeveless (7)
Sleeve Shape	Puff, Raglan, Petal, Pile (16)

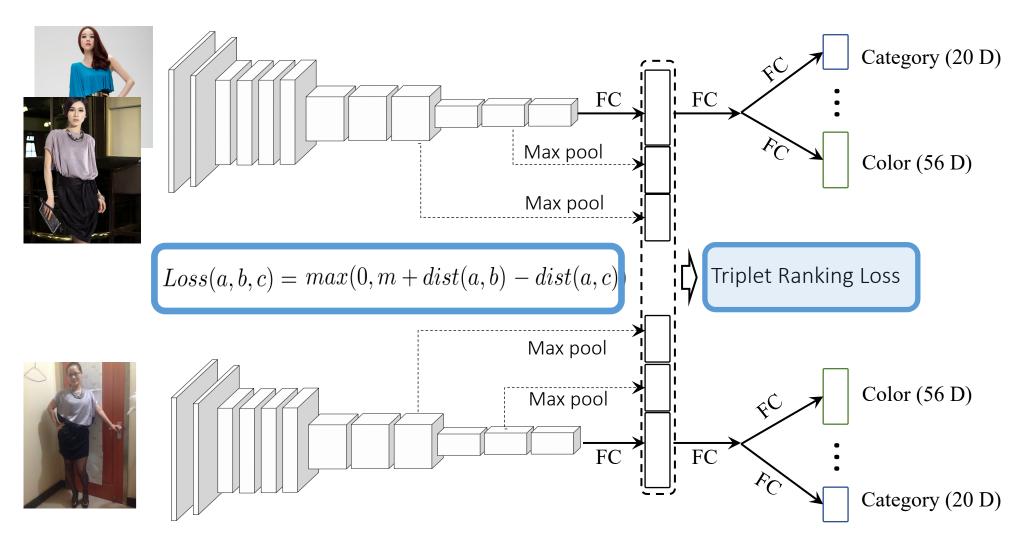
Two sub-networks to model each domain (shopping and user images)



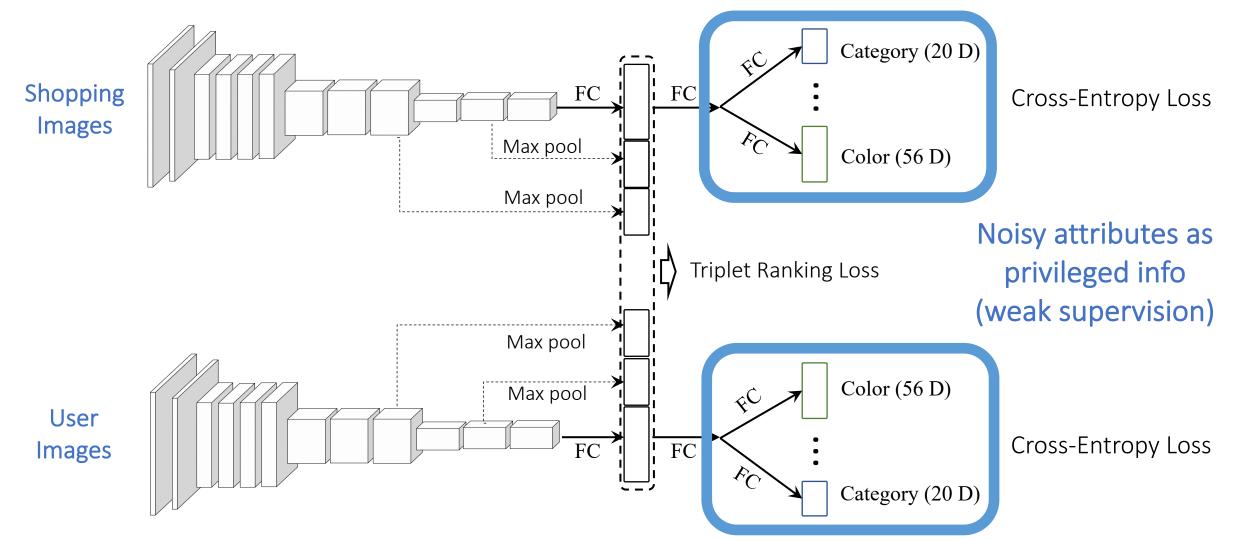
Two sub-networks to model each domain (shopping and user images)



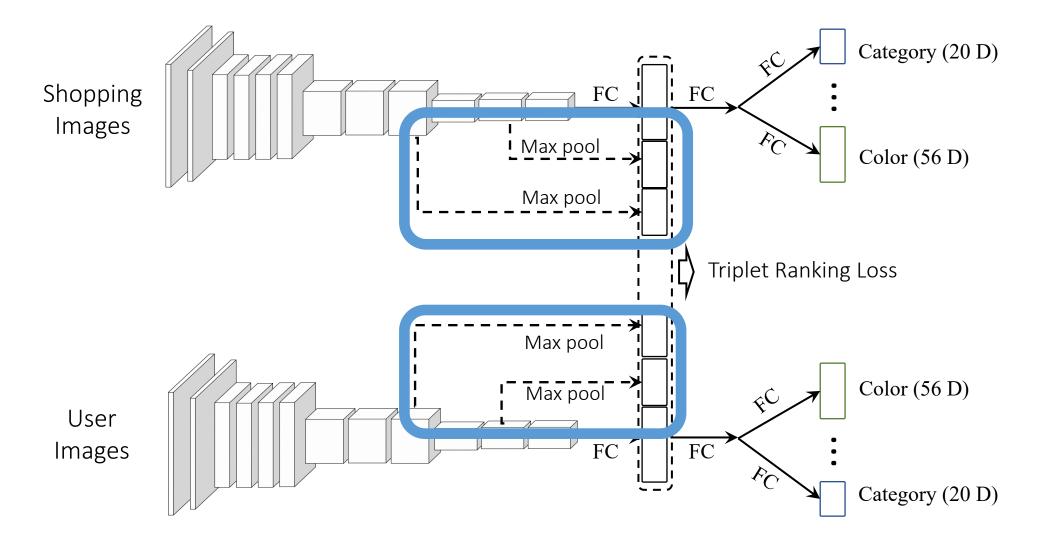
- Triplet Ranking loss function connecting the two sub-networks
- (visual similarity constraint)



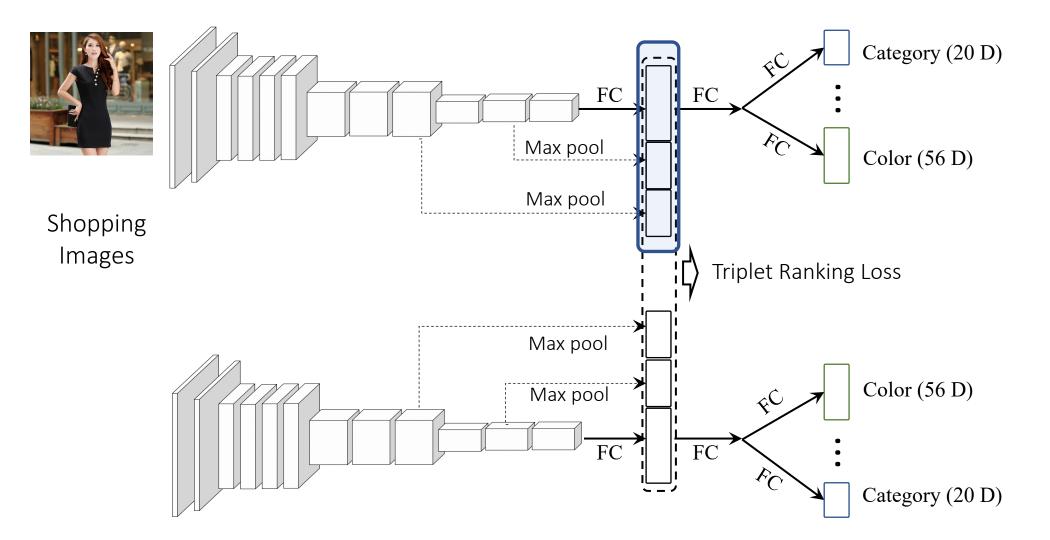
- Semantic embedding: simultaneous attribute learning and retrieval
- FC features are transmitted to multiple branches



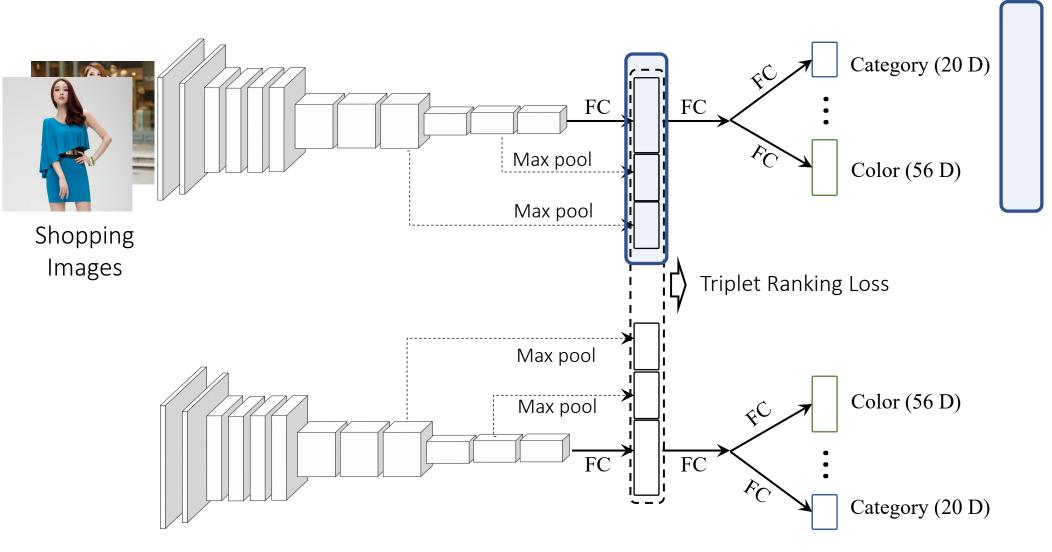
Features from conv layers for encoding more localized information



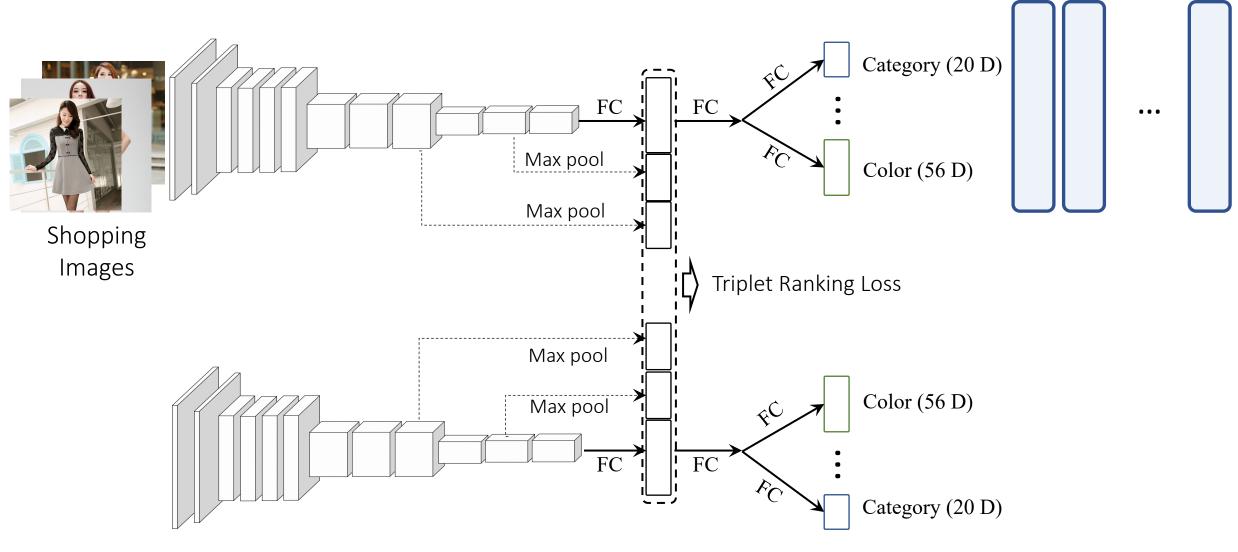
- Test time: Cross-domain Clothing Retrieval
- For each image in the gallery, compute features and store them in a database



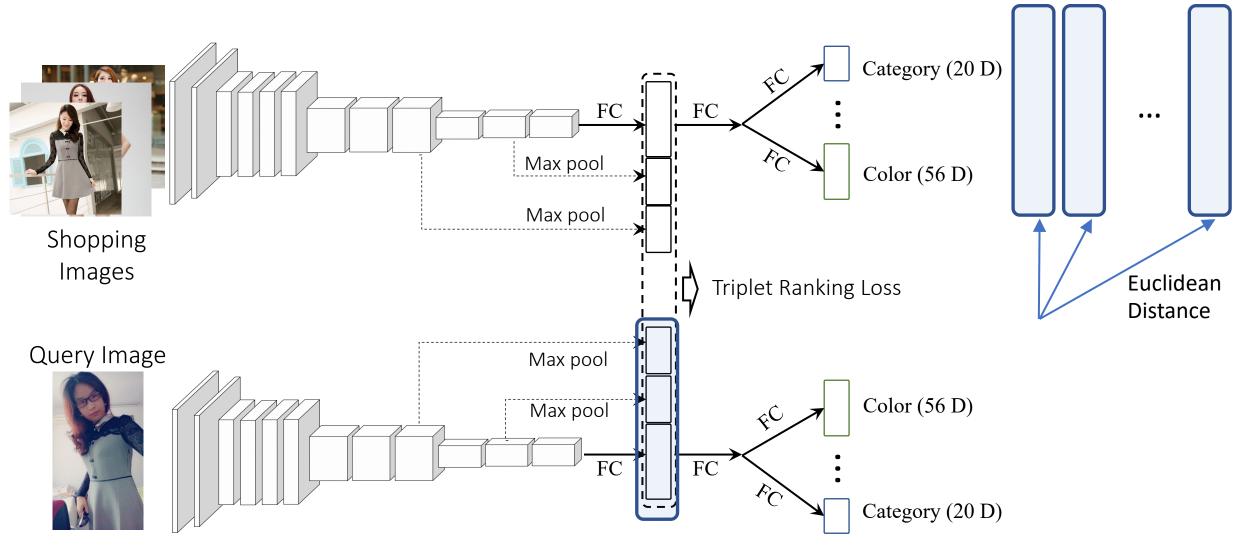
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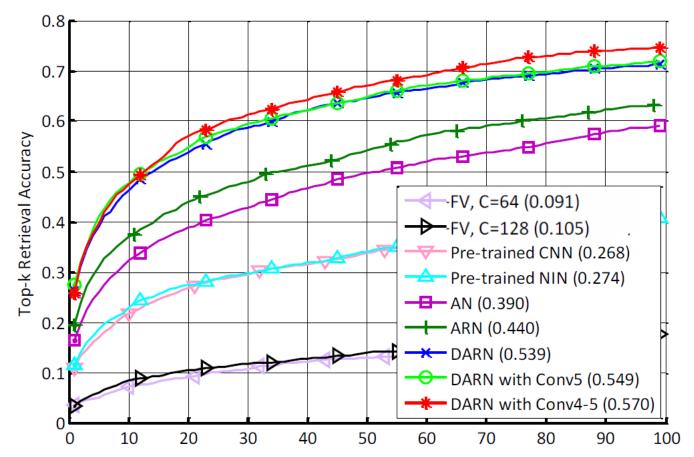
- Test time: Cross-domain Clothing Retrieval
- Given a query image, compute features and rank-order the gallery based on Euclidean distance



Experimental Results

Our method (DARN) achieves the best results compared to other state-of-the-art approaches.

Top-k retrieval accuracy on 200,000 retrieval gallery. The number in the parentheses is the top-20 retrieval accuracy.



First Column: Query Green Box: Exact same clothing

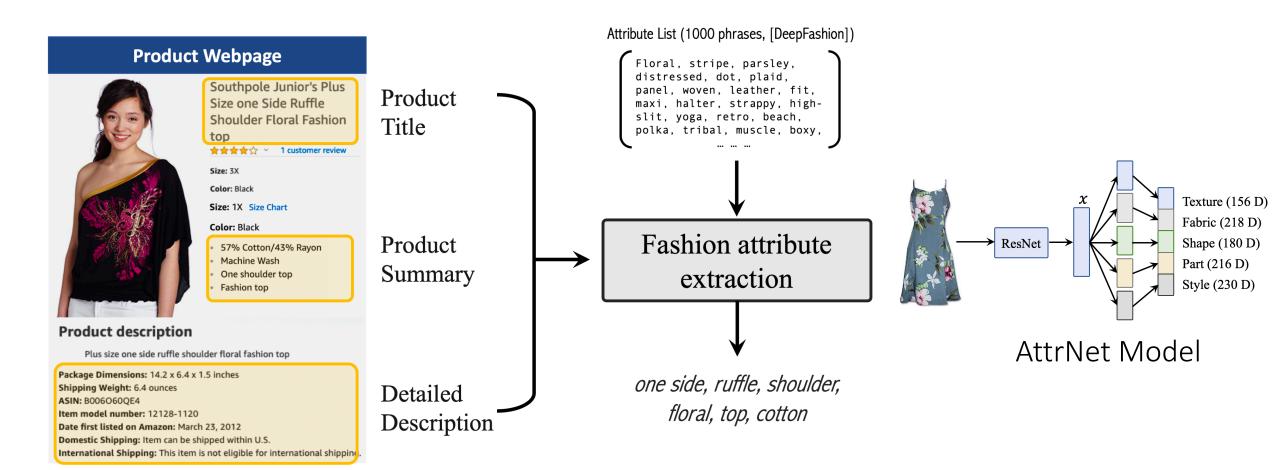


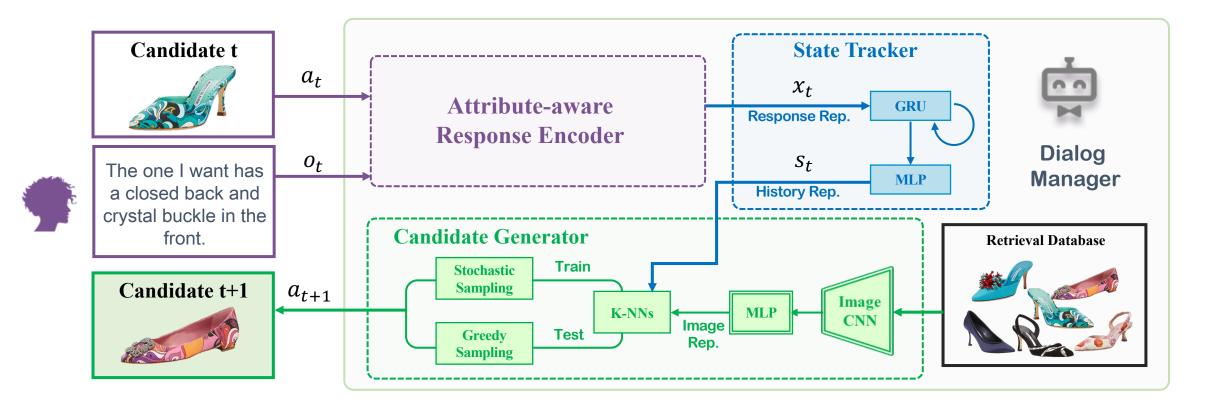
FASHION IQ DEMO

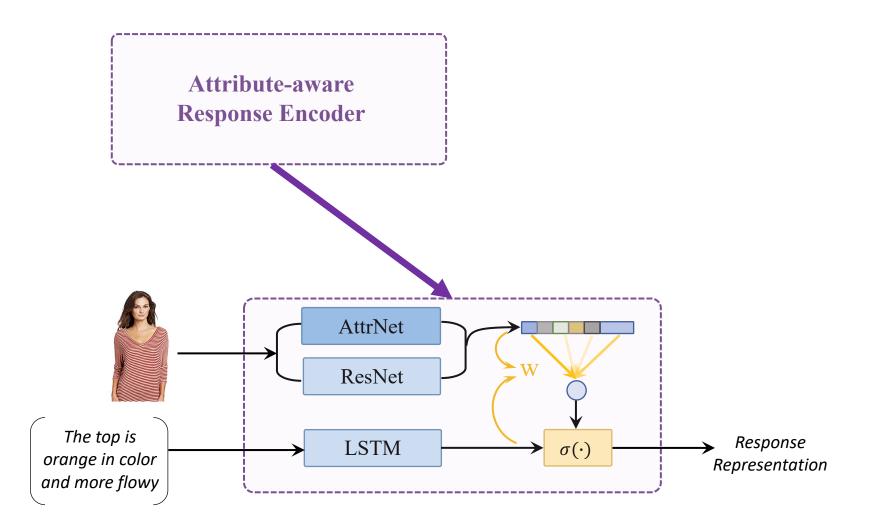
IBM RESEARCH AI

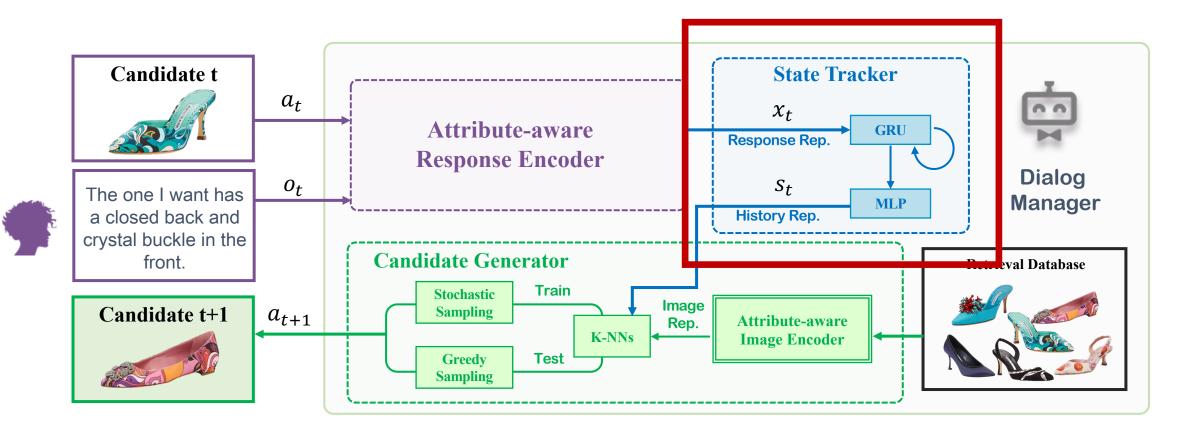
Attributes as a weak supervisory signal

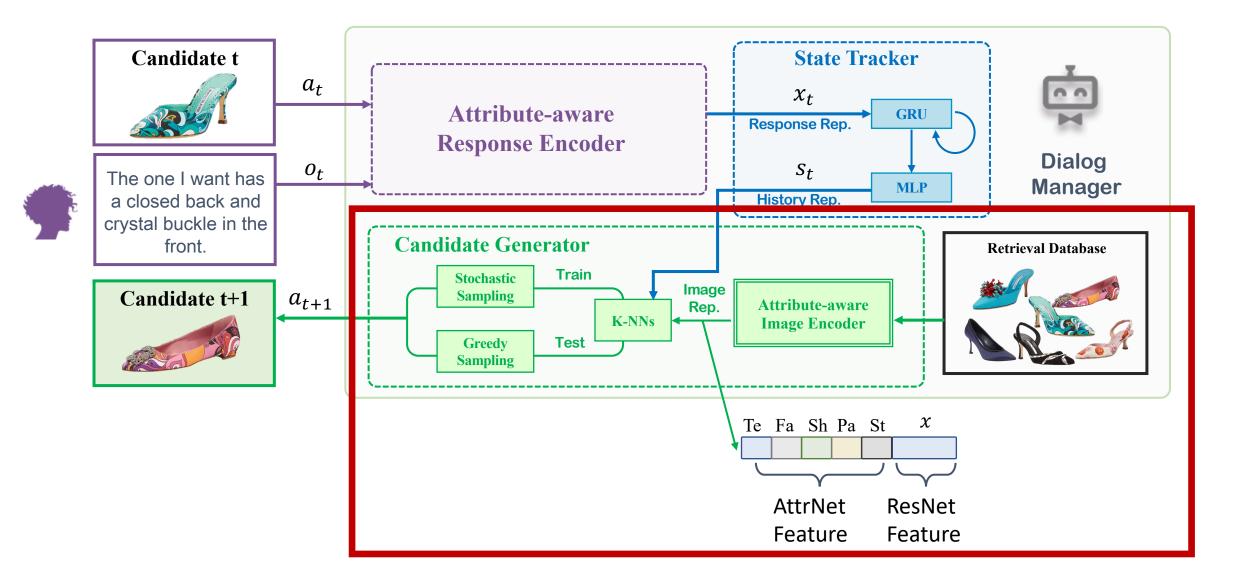
Mining attributes from text surrounding the images

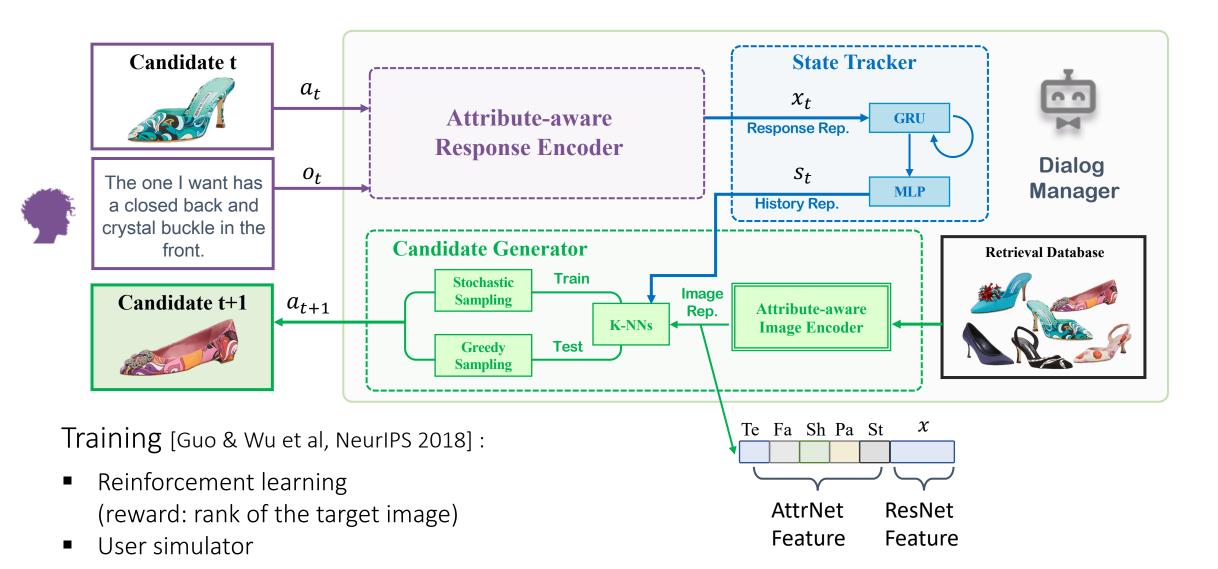




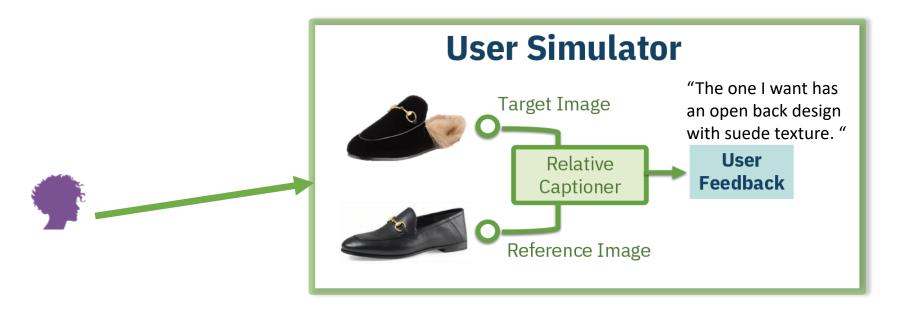




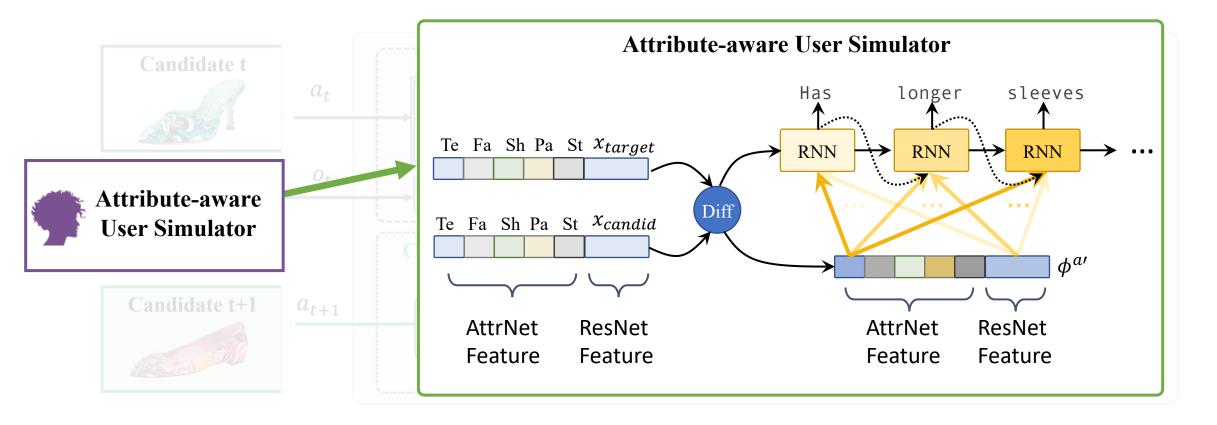




Training Dialog Manager with User Simulator



- Relative captioner: surrogate for real users
 - Automatically generates sentences describing the visual differences between target and reference images
 - New task and new dataset!



Fashion IQ Dataset

https://www.spacewu.com/posts/fashion-iq/

 Images sourced from Amazon, including three classes, Dresses, Tops & Tees, and Shirts (~60K relative captions)

	Dresses		Tops&Tees		Shirts		
	train / val / test total		train / val / test	total	train / val / test	total	
# Images	11452/3817/3818	19087	16121 / 5374 / 5374	26869	19036 / 6346 / 6346	31728	
# Images with side info	7741 / 2561 / 2653	12955	9925 / 3303 / 3210	16438	12062/4014/3995	20071	
# Relative Captions	11970 / 4034 / 4048	20052	12054 / 3924 / 4112	20090	11976/4076/4078	20130	



Relative Captions: "no sleeve flapping blouse" "it has no sleeves and it is plain"

Attribute Labels *ruffle, wash, fit*



Relative Captions: " has a blue collar" "has a blue color"

Attribute Labels cotton, twill, wash, button-front, single-button



Relative Captions: "is white with a black belt" "is lighter in color"

Attribute Labels stripe, cotton, gauze, tiered, wash, tube, braided

Results – Attribute-aware User Simulator

	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	20.3	26.5	54.1	63.3	35.3
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

(D) Dresses, (S) Shirts, (t) Tops&Tees

- Attribute-aware methods outperform image-only baselines
- Attention mechanism can better utilize the additional attribute information

Results – Interactive Image Retrieval

	Dialog Turn 1			Dialog Turn 3				Dialog Turn 5				
	Р	R@5	R@10	R@50	Р	R@5	R@ 10	R@50	Р	R@5	R@ 10	R@50
Attribute-aware (D)	90.52	4.74	7.73	23.94	98.09	26.45	36.19	67.72	98.92	40.71	52.43	79.91
with Attention (S)	90.87	2.88	4.96	17.32	98.02	18.95	27.33	55.49	98.87	29.49	40.07	69.71
(T)	90.37	3.07	5.16	17.27	98.04	21.93	30.18	59.06	99.03	36.97	47.87	77.30
Attribute-aware (D)	90.39	4.52	7.48	24.14	98.00	26.65	36.05	65.60	98.95	40.88	52.37	79.99
via Concatenation (S)	89.93	2.41	4.09	14.86	97.55	16.15	23.63	50.60	98.55	27.21	36.44	65.25
(T)	90.34	3.22	5.39	17.75	98.03	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

Attribute information and relative expressions jointly lead to better retrieval results

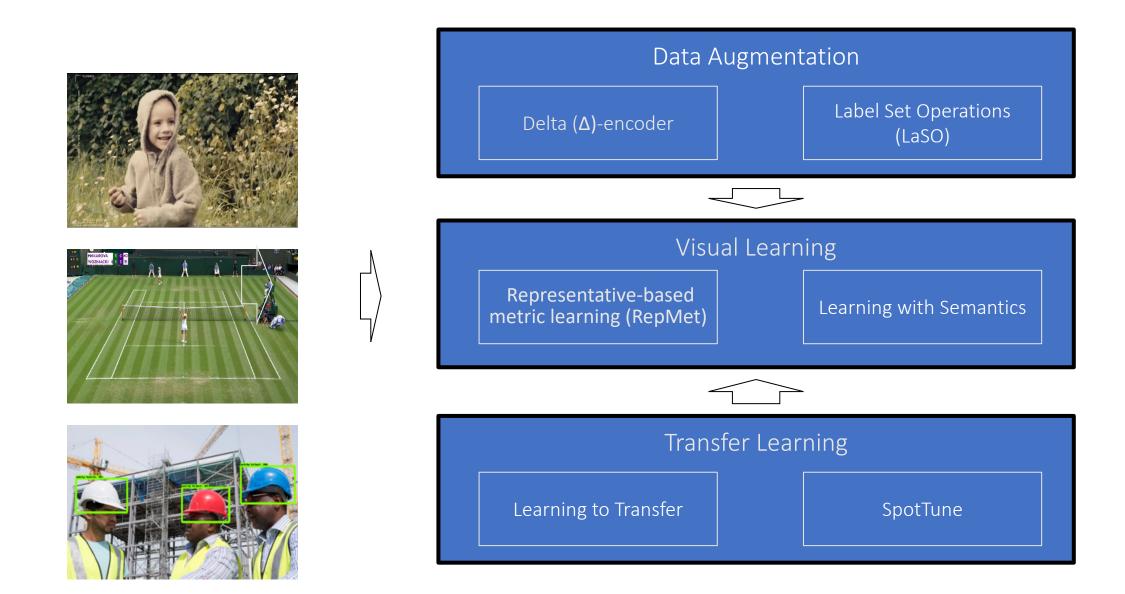
 More advanced techniques for composing side information, relative feedback and image features could lead to further performance gains.



Weak supervised learning for fashion search

Learning with less labels beyond weak supervision

IBM Research AI – Learning with Less Labels for Vision



Transfer Learning

Model Selection [Dube et al, Deep Vision Workshop 2019] Source Task Food Building Nature Sports Target Which layers to freeze and which layers to fine-tune? Fruit Task (per instance) Animals Fungus Plant Training People 10 Example Freeze Freeze Free Furniture Garment Music Training Example Fabric Weapons Tool

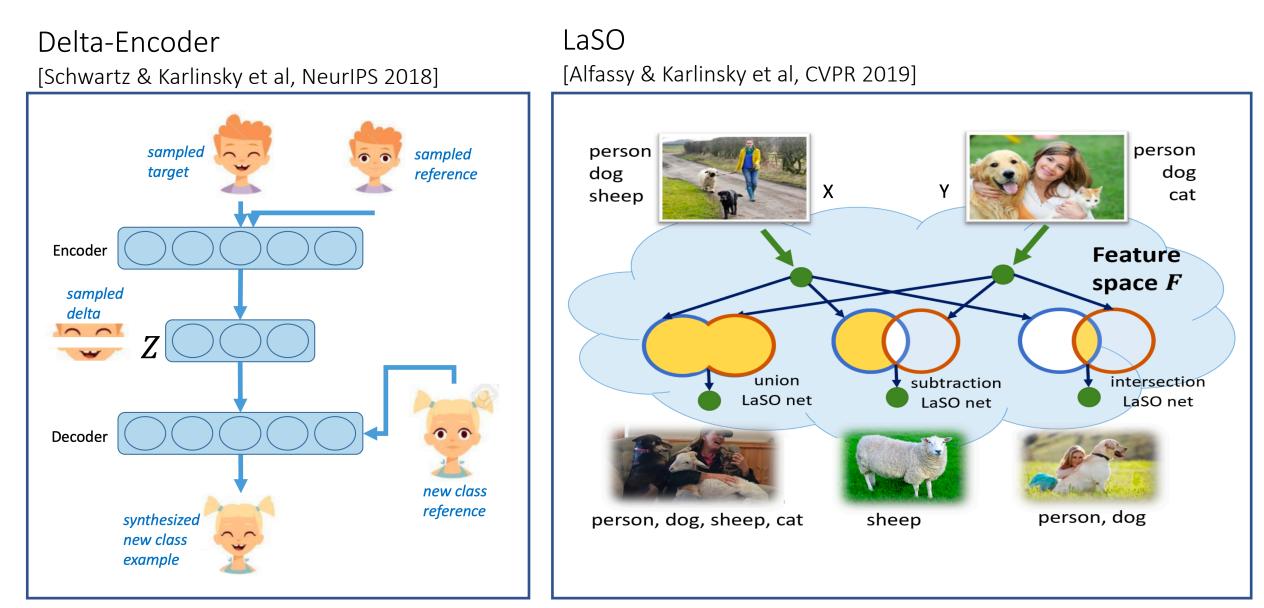
SpotTune [Guo et al, CVPR 2019]

Fine-tune Fine-tune Freeze Freeze

Transfer pre-trained parameters to new task

Fine-tune Fine-tune

Sample Synthesis for Few-Shot Learning



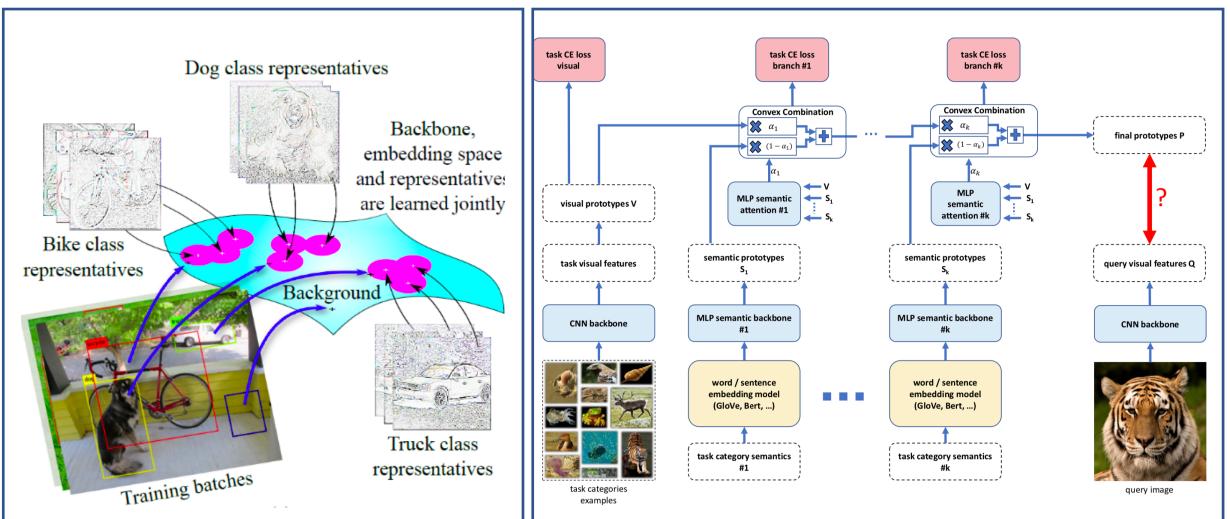
Few-shot Learning

RepMet

[Karlinsky et al, CVPR 2019]

Learning with Semantics

[Schwartz & Karlinsky et al, Language & Vision Workshop, 2019]



Summary

- Takeaway message: Noisy visual attribute labels mined from the web are useful as *privileged information* during training to improve image search:
 - Street2Shop fashion retrieval [Huang et al, ICCV 2015]
 - Dialog-based interactive fashion retrieval [Guo & Wu et al, NeurIPS 2018] [Guo & Wu et al, 2019]
- Check out our recent work on learning with less labels @CVPR

IBM Research AI: Learning More from Less in Vision @ CVPR

- 1. A. Alfassy, L. Karlinsky, A. Aides, J. Shtok, S. Harary, R. Feris, R. Giryes, A. M. Bronstein, "LaSO: Label-Set Operations network for multi-label few-shot classification," *CVPR-2019*, June 2019.
- 2. L. Karlinsky, J. Shtok, S. Harary, E. Schwartz, A. Aides, R. Feris, R. Giryes, A. M. Bronstein, "RepMet: Representative-based metric learning for classification and one-shot object detection", *CVPR-2019*, June 2019.
- 3. Y. Guo, H. Shi, A. Kumar, K. Grauman, T. Rosing, R. Feris, "SpotTune: Transfer Learning through Adaptive Fine-Tuning," *CVPR-2019*, June 2019.
- 4. E. Schwartz, L. Karlinsky, R. Feris, R. Giryes, A. Bronstein, "Baby steps towards few-shot learning with multiple semantics," *Language and Vision Workshop at CVPR-2019*, June 2019.
- 5. P. Dube, B. Bhattacharjee, S. Huo, P. Watson, B. Belgodere, J. R. Kender, "Automatic Labeling of Data for Transfer Learning", Deep Vision Workshop at CVPR-2019, June 2019.