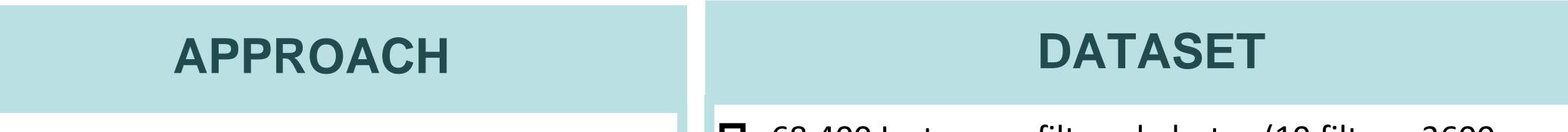


# Filter Recommendation through Analyzing Objects, Scenes and Aesthetics

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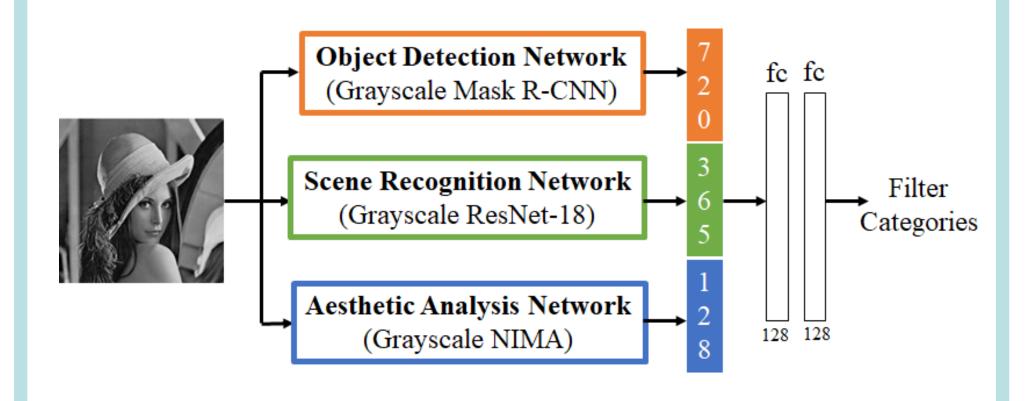
Goal: Automatic selection of photo filters based on photo content

- Demonstrate how filtered images on Instagram can be used for training a filter recommendation model
- Use high level image representation for predicting proper filters



#### Filter Recommendation Network

- ✓ Objects: Mask R-CNN + MS COCO
- ✓ Scenes: Res-18 + Places365
- Aesthetic attributes: NIMA + AVA



# Style invariant representation

- Extract from grayscale images
- Fine-tune the networks using grayscale images

Object detection performance on MSCOCO

| Model                | $AP^{bb}$ | $AP_{50}^{bb}$ | $AP_{75}^{bb}$ |
|----------------------|-----------|----------------|----------------|
| Mask R-CNN           | 38.2      | 60.3           | 41.7           |
| Grayscale Mask R-CNN | 33.9      | 51.4           | 37.4           |

68,400 Instagram filtered photos (19 filters, 3600 photos per filter type)

|               | Pros  | Cons  |
|---------------|---|---|
| Instagram     | <ul><li>Low-cost collection</li><li>High diversity</li></ul>  | <ul> <li>No original photo</li> <li>One filter per photo<br/>(decided by user)</li> </ul> |
| FACD [Sun 17] | <ul> <li>Original photo available</li> <li>Multiple filters per<br/>photo (decided by AMT)</li> </ul> | <ul> <li>High cost of ground<br/>truth construction</li> <li>Low quantity</li> </ul>      |

[Sun 17] W. -T. Sun, T. -H. Chao, Y. -H. Kuo, Winston Hsu. Photo Filter Recommendation by Category-Aware Aesthetic Learning. *IEEE Trans. on Multimedia*, 2017.

## RESULTS

## **Recommendation results on FACD**

| Model                                 | Top-1 Accuracy (%) | Top-3 Accuracy (%) |
|---------------------------------------|--------------------|--------------------|
| AlexNet [3]                           | 33.13              | 70.63              |
| RAPID net [4]                         | 37.50              | 72.50              |
| Category-aware learning (AlexNet) [2] | 41.25              | 80.00              |
| Category-aware learning (RAPID) [2]   | 41.88              | 79.50              |
| Ours (Scene + Aesthetics)             | 51.25              | 80.00              |

The proposed method achieved the best performances in both of top-1 and top-3 predictions. The gain was significant on the top-1 accuracy (over 9%).

#### Effects of different features

| Model                       | Top-1 Accuracy (%) | Top-3 Accuracy (%) |
|-----------------------------|--------------------|--------------------|
| Object                      | 43.75              | 76.25              |
| Scene                       | 48.12              | 79.37              |
| Aesthetics                  | 51.25              | 75.62              |
| Object + Scene              | 45.00              | 75.62              |
| Object + Aesthetics         | 51.87              | 77.50              |
| Scene + Aesthetics          | 51.25              | 80.00              |
| Object + Scene + Aesthetics | 46.87              | 75.00              |

Scene recognition performance on Places365

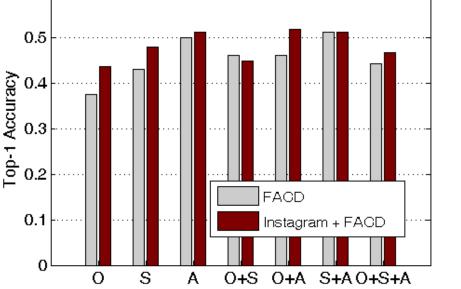
| Model               | Top-1 acc. | Top-5 acc. |
|---------------------|------------|------------|
| ResNet-18           | 54.74%     | 85.08%     |
| Grayscale ResNet-18 | 51.00%     | 82.00%     |

Aesthetic quality estimation performance on AVA

| Model          | Top-1 acc. |
|----------------|------------|
| NIMA           | 57.84%     |
| Grayscale NIMA | 56.43%     |

Mei-Chen Yeh (myeh@csie.ntnu.edu.tw) http://www2.csie.ntnu.edu.tw/~myeh Our approach using a single type of feature outperformed previous approaches; scenes and the aesthetics outperformed objects.

#### **Does Instagram filtered images help?**



The use of Instagram filtered images alleviated the filter recommendation task.