Predicting aesthetic appreciation of images

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NAVER LABS Europe
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Data-driven approaches to aesthetic prediction

Most prediction problems in computer vision involve largely objective properties:

- Object recognition
- Semantic segmentation
- Local feature matching
- Etc.

... and are successfully tackled using data-driven, machine learning methods.

Can we learn models for visual aesthetics using data-driven methods?

Data-driven approaches to aesthetic prediction

Requirements for data-driven aesthetic prediction:

- Annotated datasets
- Effective image representations

Global outline

AVA: A large-scale dataset for aesthetic visual analysis
Collaborators:
Luca Marchesotti
Florent Perronnin

A deep architecture for unified aesthetic prediction
Collaborators:
Albert Gordo

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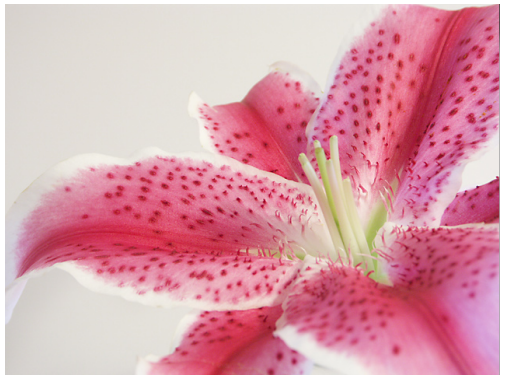
Aesthetic prediction

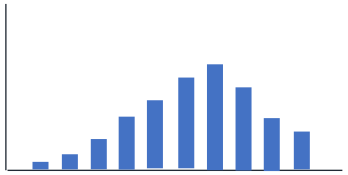
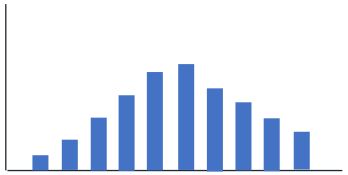
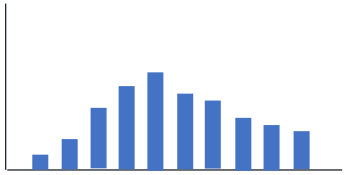
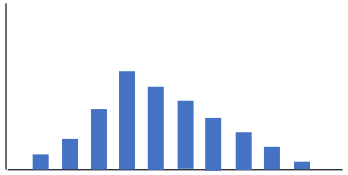



Binary classification


Mean score prediction

7.65 **6.32** … **4.81** **4.15**

Score distribution prediction

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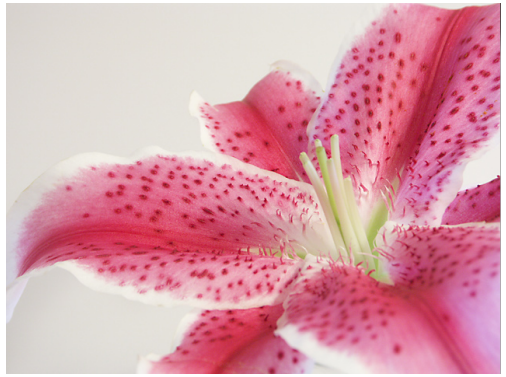
Machine learning-based approaches

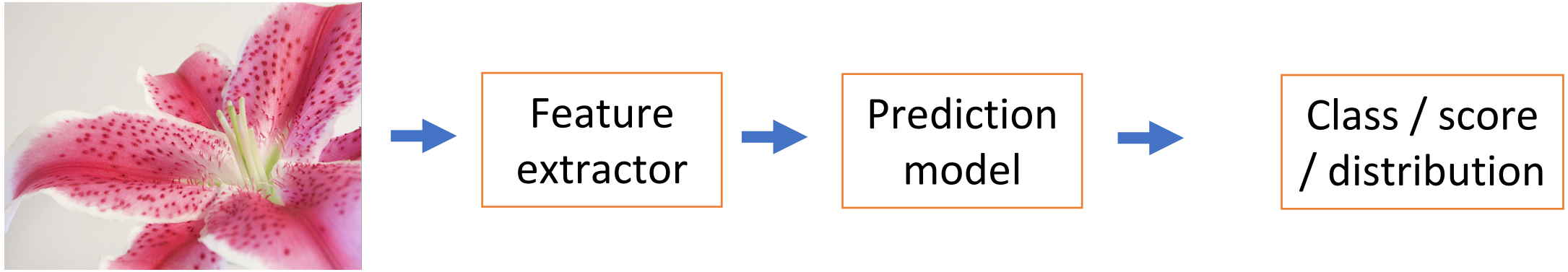


Feature extractor

Prediction model

Class / score / distribution

Machine learning-based approaches

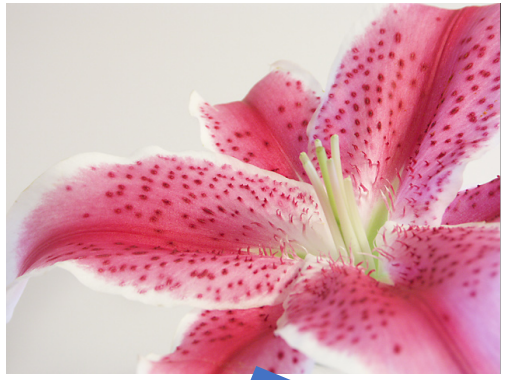


Features:

- Handcrafted for aesthetics: e.g. color histograms, saturation, composition [1]
- Generic: e.g. SIFT features [2]

[1] Datta et al. Studying aesthetics in photographic images using a computational approach. ECCV 2006.
[2] Marchesotti et al. Assessing the aesthetic quality of photographs using generic image descriptors. ICCV 2011.

Machine learning-based approaches



Feature extractor

Prediction model

Class / score / distribution

Deep model
(feature extractor / predictor)

Data for training aesthetic prediction models

Aesthetic appreciation is ***subjective***, i.e. there is no “right” answer.

Most annotations capture a consensus opinion or statistic, *i.e.* “How would most people score or label this image?”

Because of subjectivity, training requires large-scale data:

- Large number of images
- Large number of annotations per image

Data for training aesthetic prediction models

Public datasets collect data from 3 main sources:

Flickr:
- Image-sharing website
- Users can rate images from 1-5 stars

Photo.net:
- Online community for photographers
- Images are scored from 1-7

Dpchallenge:
- Online community for photographers
- Photography challenges are central
- Submissions are scored from 1-10

DPChallenge.com

TITLE: Skyscape

Description:

Make the sky the subject of your photo this week.

Stats

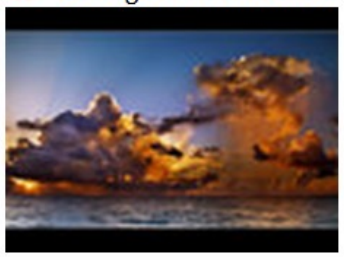
Voting Dates:
13/07/2010 - 19/07/2010

Numbers & Statistics:
Submissions: 136
Disqualifications: 1
Votes: 16,009
Comments: 595

Average Score: 5.64014

1st place with an average vote of **7.4831**

2nd place with an average vote of **7.0328**



3rd place with an average vote of **6.9333**

4th place with an average vote of **6.8547**

5th place with an average vote of **6.7073**

6th place with an average vote of **6.6667**

7th..

8th..

9th..

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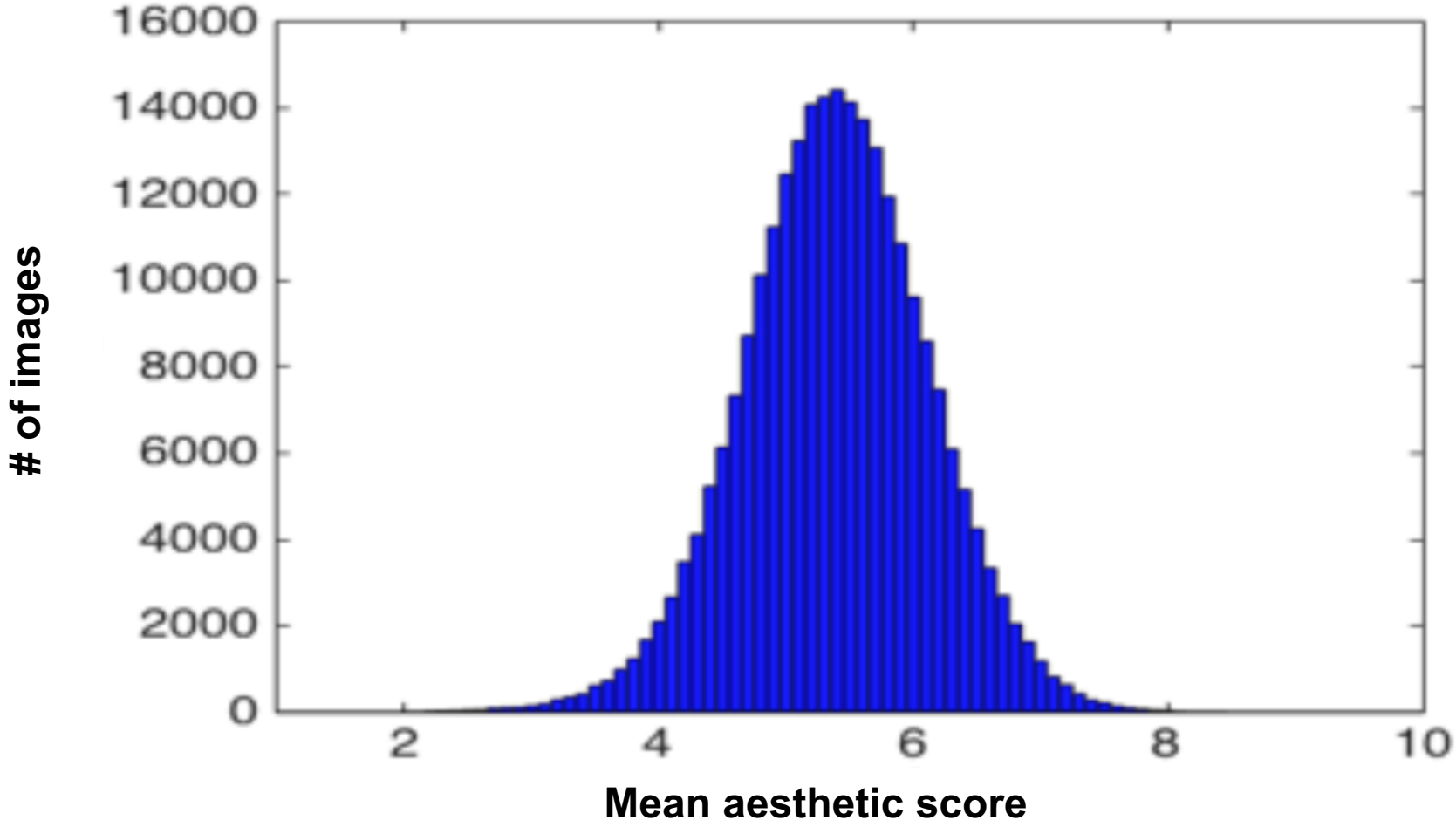
AVA: A large-scale dataset for aesthetic visual analysis

AVA [1,2] at a glance:

- # of images: approx. 255K
- # of associated challenges: 963
- # of votes per image: 78 – 549 (210 on average)
- Semantic annotations: approx. 200K images with 1 tag; 66 tags in total
- Weak style annotations: 14K images annotated with 14 style categories
- Weak textual annotations: 2.9M comments

[1] Murray et al. AVA: A Large-Scale Database for Aesthetic Visual Analysis. CVPR 2012.
[2] Marchesotti et al. Discovering beautiful attributes for aesthetic image analysis . IJCV 2015.

AVA: mean score distribution



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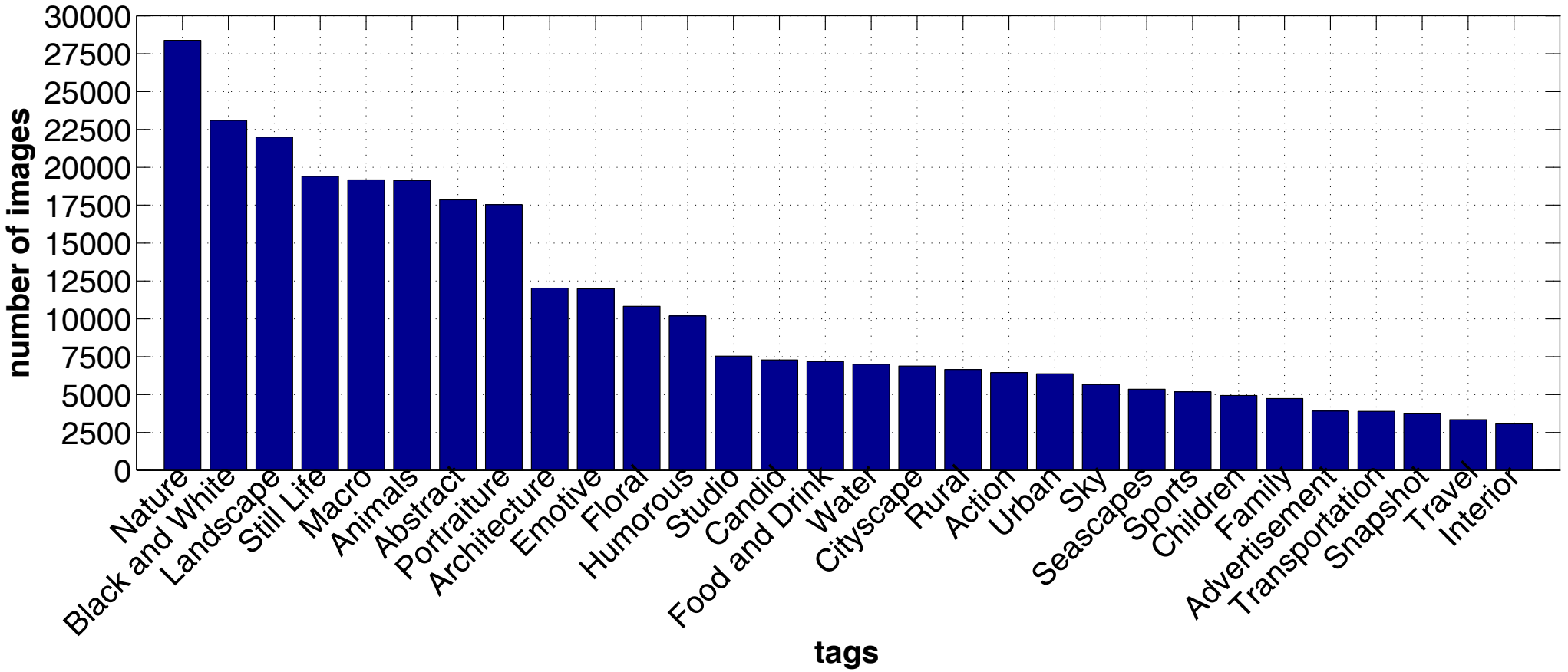
AVA: distribution of semantic labels



Note: Max 2 tags / image

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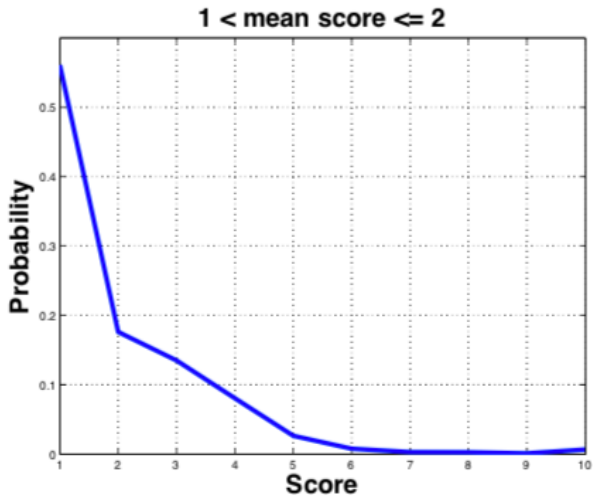
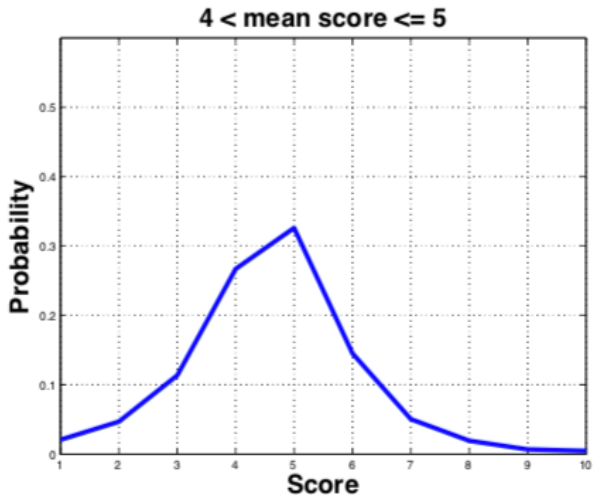
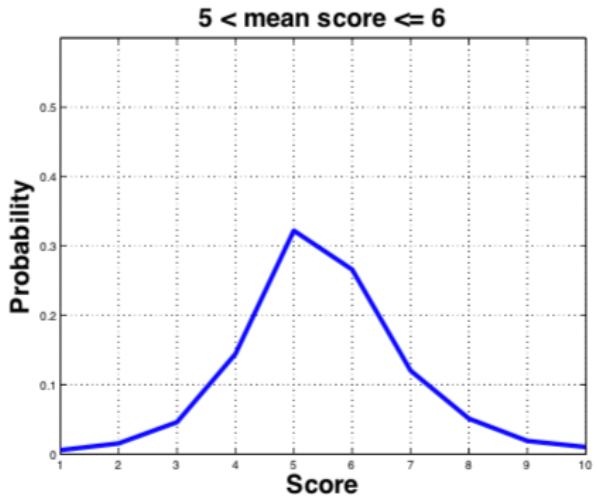
Averaged distributions for images with different mean scores



(a)



(b)



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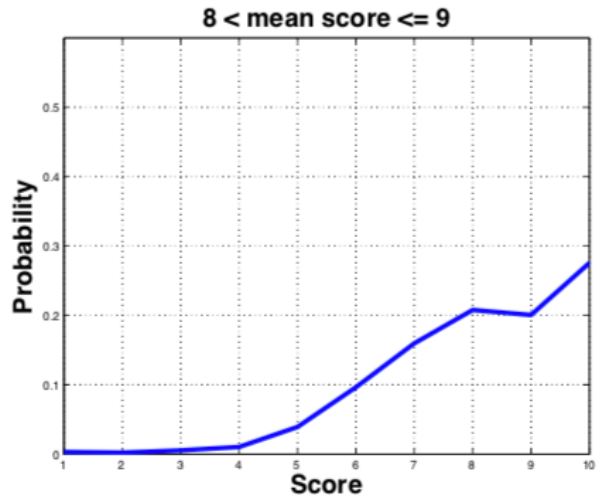

(d)

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Modelling score distributions

We fit several probability distribution models to our distributions:

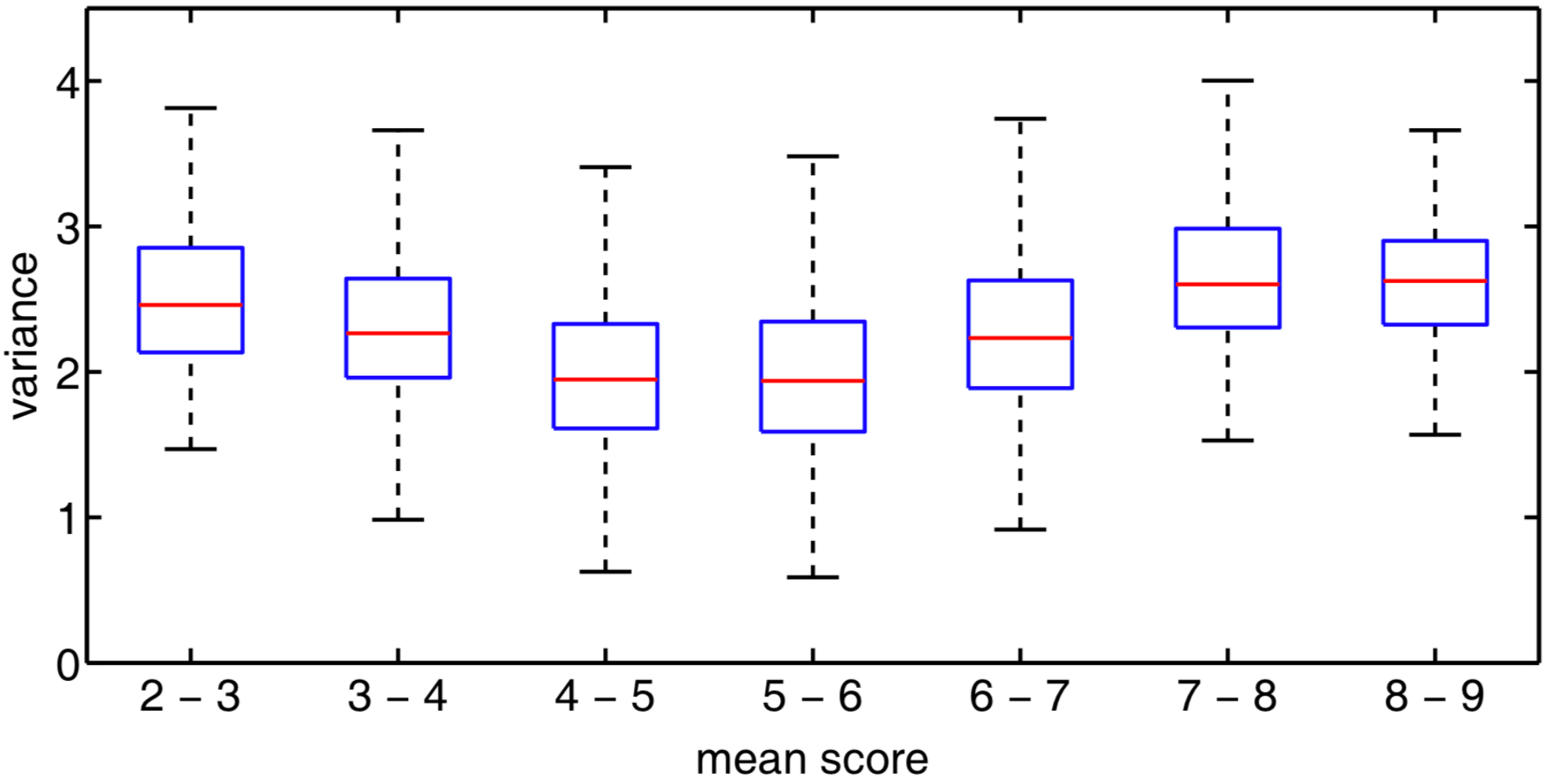
- Gaussian, Beta, Weibull and Generalized Extreme Value
- Gaussian functions perform adequately for most images
- Floor / ceiling effect at extremes of rating scale [1]
  - Better modelled with a Gamma distribution (Γ)

[1] Cramer & Howitt. The SAGE dictionary of statistics, 1st edn. 2004. p. 21 (entry “ceiling effect”), p. 67 (entry “floor effect”)

Modelling score distributions

Mean score	Average RMSE		
	Gaussian	Γ	Γ'
1-2	0.1138	**0.0717**	0.1249
2-3	0.0579	**0.0460**	0.0633
3-4	**0.0279**	0.0444	0.0325
4-5	**0.0291**	0.0412	0.0389
5-6	**0.0288**	0.0321	0.0445
6-7	0.0260	**0.0250**	0.0455
7-8	**0.0268**	0.0273	0.0424
8-9	0.0532	0.0591	**0.0403**
Average RMSE	**0.0284**	0.0335	0.0429

Variance of score distributions



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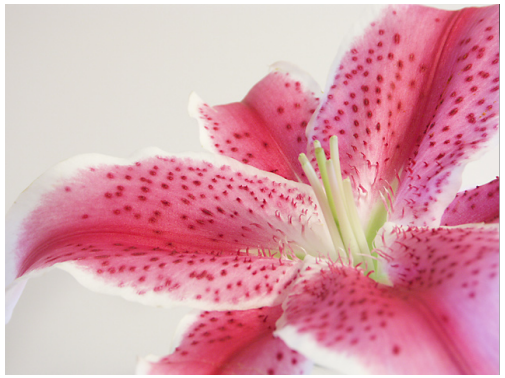
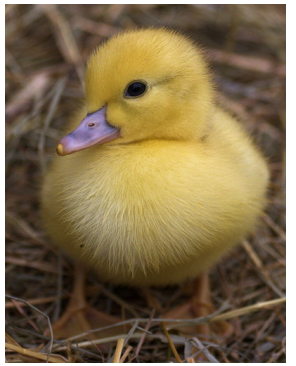
Aesthetic visual analysis






Binary classification


Mean score prediction

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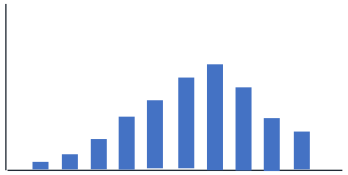
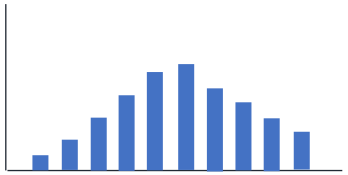
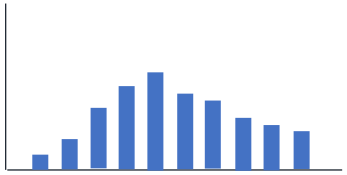
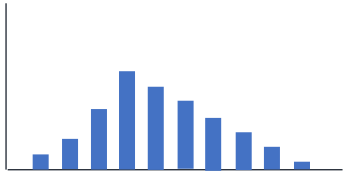
Score distribution prediction

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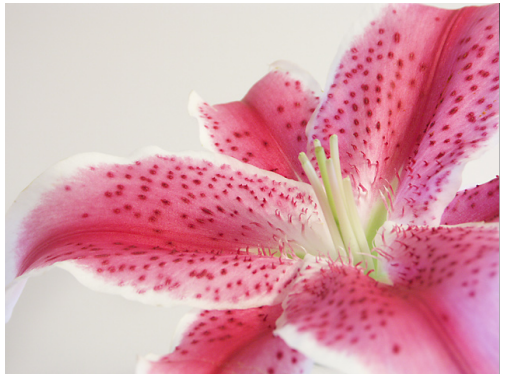
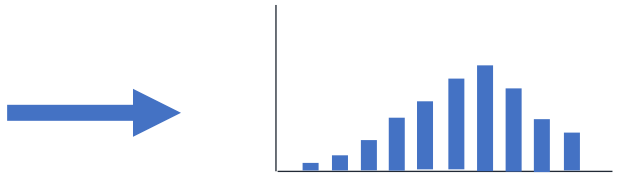
Obtaining annotations for AVA





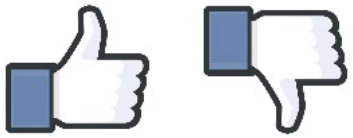
Score distribution

Calculate mean

7.65

Mean score

Apply threshold



Binary class

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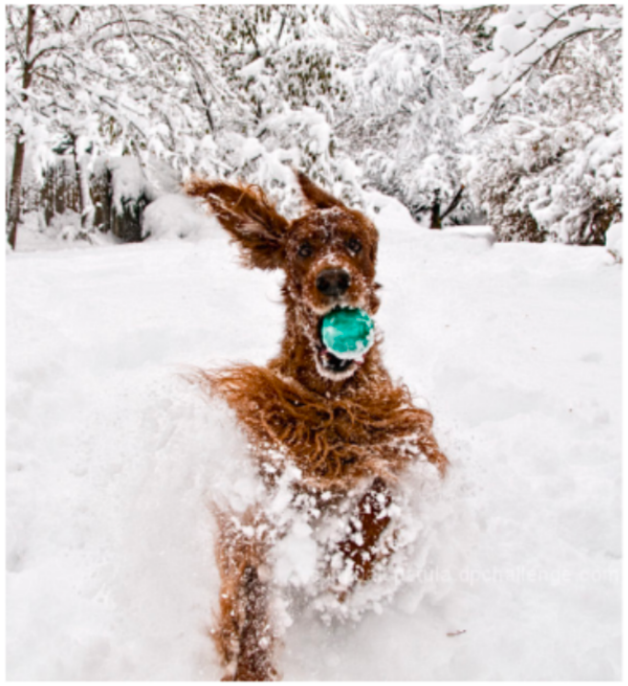
Obtaining annotations for AVA

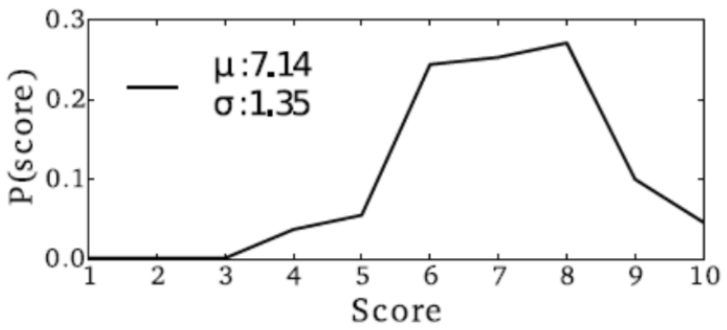
Most works perform binary prediction

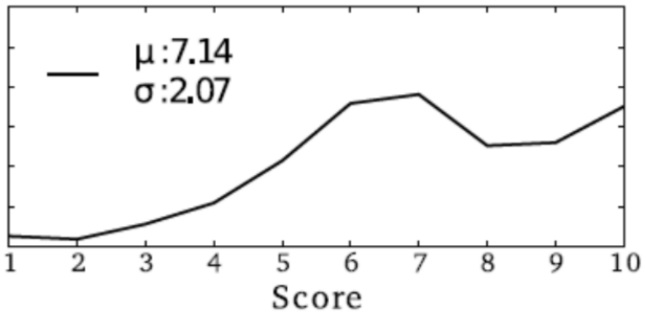
But …

Score distributions are

more informative







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Predicting aesthetic score distributions

Previous work:

- Wu et al. [1]:
  - Used traditional features
  - Focused on mitigating unreliable scores from annotators using reweighting
- Jin et al. [2]:
  - Used deep model and χ^2error
  - Focused on reweighting samples to mitigate imbalance in score distribution of training set

Our approach [3]:

- Uses deep architecture
- Explores how to leverage semantic information

[1] Wu et al. Learning to predict the perceived visual quality of photos. ICCV 2011.
[2] Jin et al. Image aesthetic predictors based on weighted cnns. ICIP 2016.
[3] Murray & Gordo. A deep architecture for unified aesthetic prediction. arXiv 2017.

Leveraging semantic information

Aesthetic properties are dependent on image content

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Leveraging semantic information for deep learning

No large-scale aesthetics datasets exist that also have semantic annotations

- AVA is only partially-annotated (max 2 tags from a predefined list)

Recent works incorporate semantic information by using:

- Weak labels [1]:
  - Cluster images and use cluster IDs as semantic label
  - Train network for auxiliary task of predicting weak semantic labels
- Auxiliary networks [2]:
  - Use output from scene categorizer as additional features

[1] Mai et al. Composition-preserving deep photo aesthetics assessment. CVPR 2016.
[2] Kong et al. Photo aesthetics ranking network with attributes and content adaptation. ECCV 2016.

Leveraging semantic information

Our approach - Inspired by “model distillation” [1]:

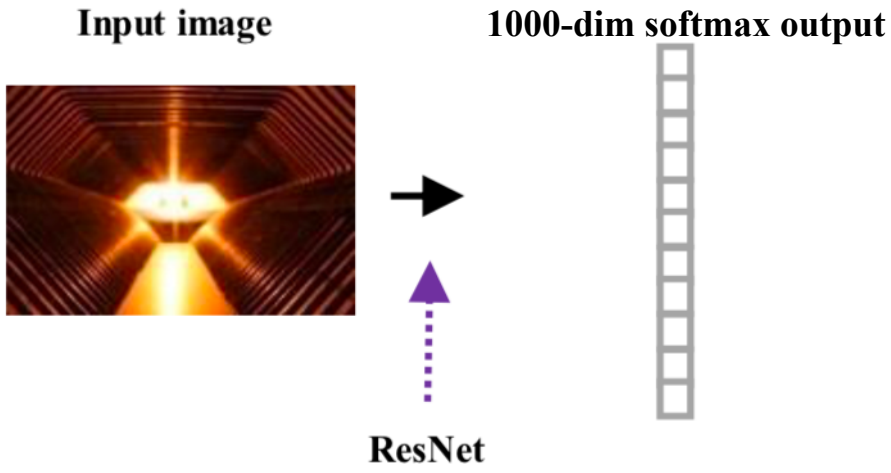
- In a nutshell, use a trained “teacher network” to supervise a “student” network:
  - The softmax output of the teacher network is used as the target for training the student
  - Conceived for network compression, *i.e.* student network is usually more compact than original teacher network
- We use a teacher network, trained for ImageNet classification, to:
  - Provide semantic pseudo-ground-truth in the form of softmax probabilites.
  - Pre-train the weights of our aesthetic prediction model, i.e. provide a better initialization.

[1] Hinton et al. Distilling the knowledge in a neural network. NIPS Deep Learning and Representation Learning Workshop, 2014.

Leveraging semantic information

Our approach in detail:

1. Extract softmax result from original ResNet model trained on ImageNet



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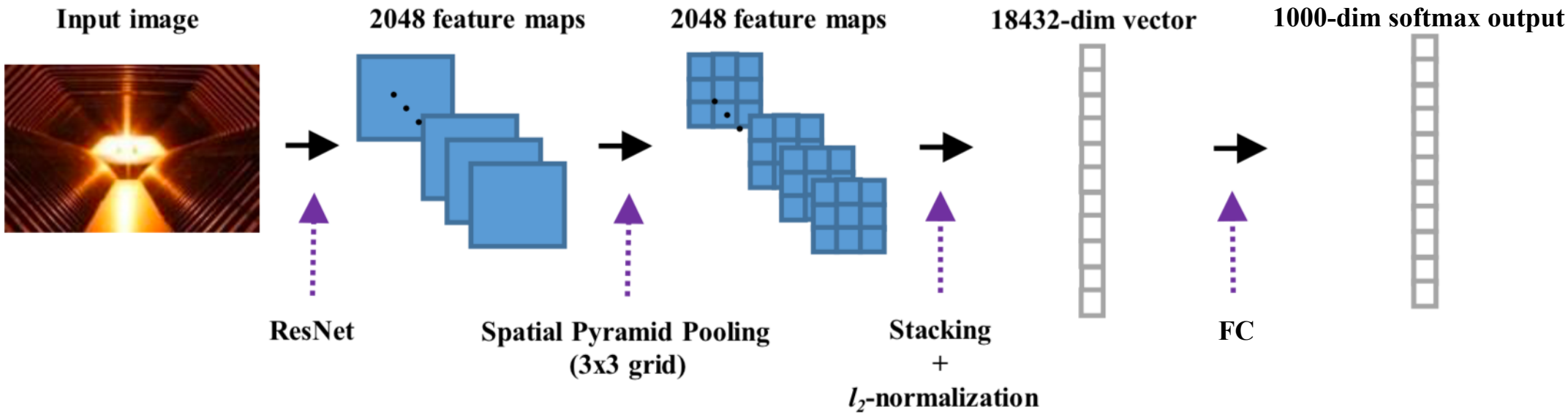
Leveraging semantic information

Our approach in detail:

2. Train modified architecture using softmax result as target



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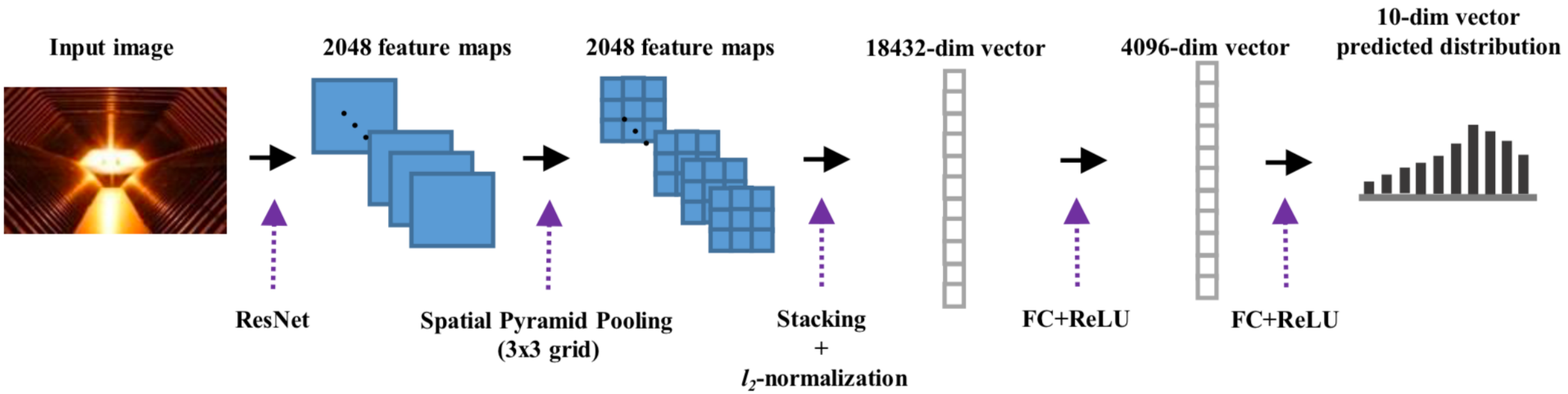
Leveraging semantic information

Our approach in detail:

3. Fine-tune previous model for score distribution prediction



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Experiments

We evaluated our learned model on 3 tasks:

- Aesthetic quality (binary) classification
- Aesthetic mean score prediction
- Aesthetic score distribution prediction

Experiments

Comparing different variants of the proposed approach:

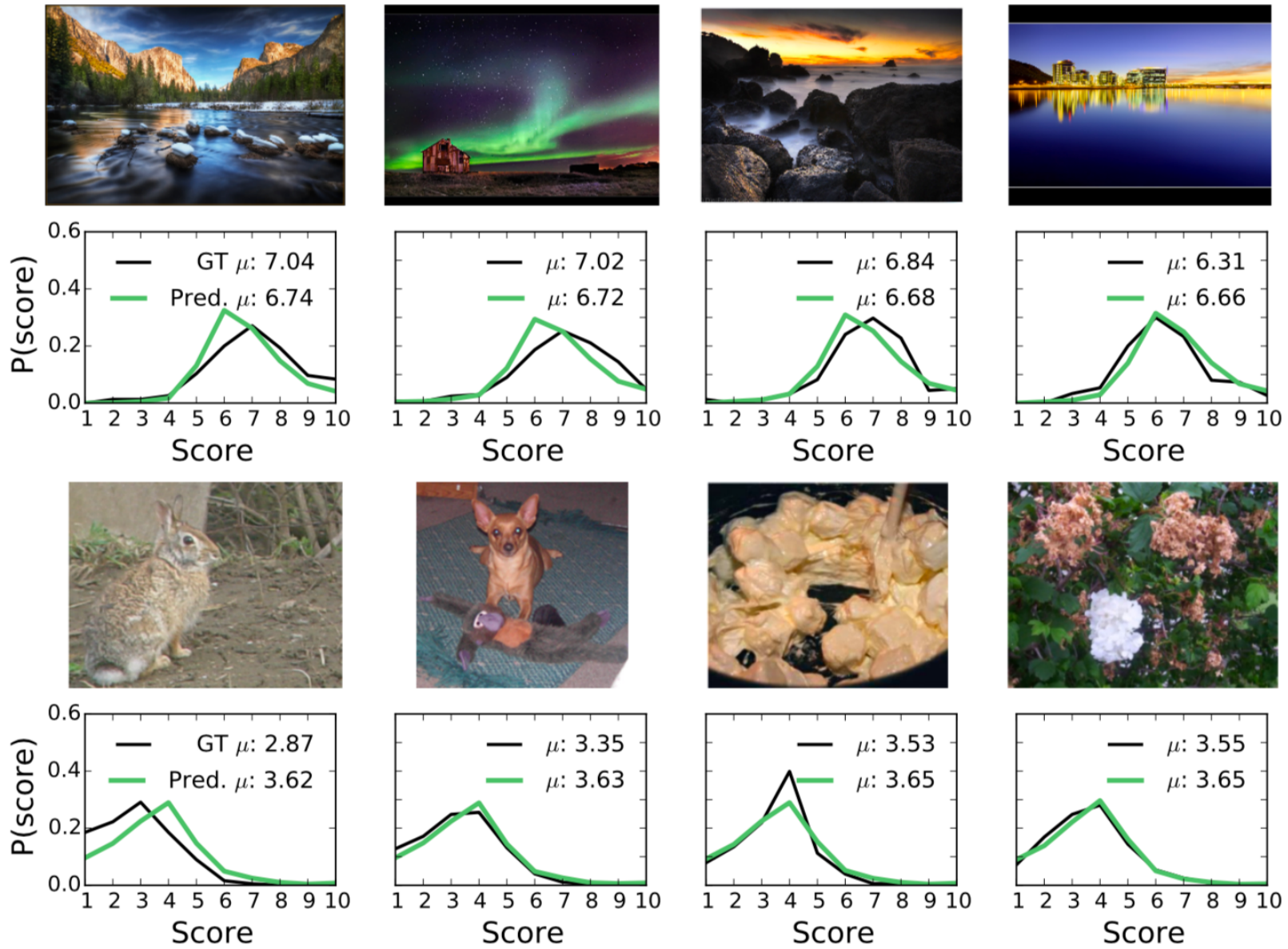
Method	KLDIV ↓	CDLoss ↓	MSE ↓	ρ ↑	Acc.(%) ↑
VGG-ImN-mean	-	-	0.314	0.659	78.4
VGG-ImN-dist-Eucl.	0.134	0.0821	0.383	0.560	76.3
VGG-ImN-dist	0.128	0.0673	0.311	0.665	78.7
ResNet-ImN-dist	0.105	0.0618	0.285	0.702	79.7
ResNet-AVA-dist	0.104	0.0609	0.280	0.707	79.8
ResNet-AVA-dist-m	**0.103**	**0.0607**	**0.279**	**0.709**	**80.3**

Experiments

Comparing to state-of-the-art methods:

Method	CDLoss ↓	MSE ↓	ρ ↑	Acc.(%) ↑
Wu *et al.* [44]†	0.1061	-	-	-
Jin *et al.* [16]-HP †	-	0.636	-	-
Jin *et al.* [16]-Reg †	-	0.337	-	-
Mai *et al.* [30]	-	-	-	77.4
Kong *et al.* [21]	-	-	0.558	77.8
Zhou *et al.* [46]	-	-	-	78.2
`VGG-ImN-dist`	0.0673	0.311	0.665	78.7
APM	**0.0607**	**0.279**	**0.709**	**80.3**

Qualitative results



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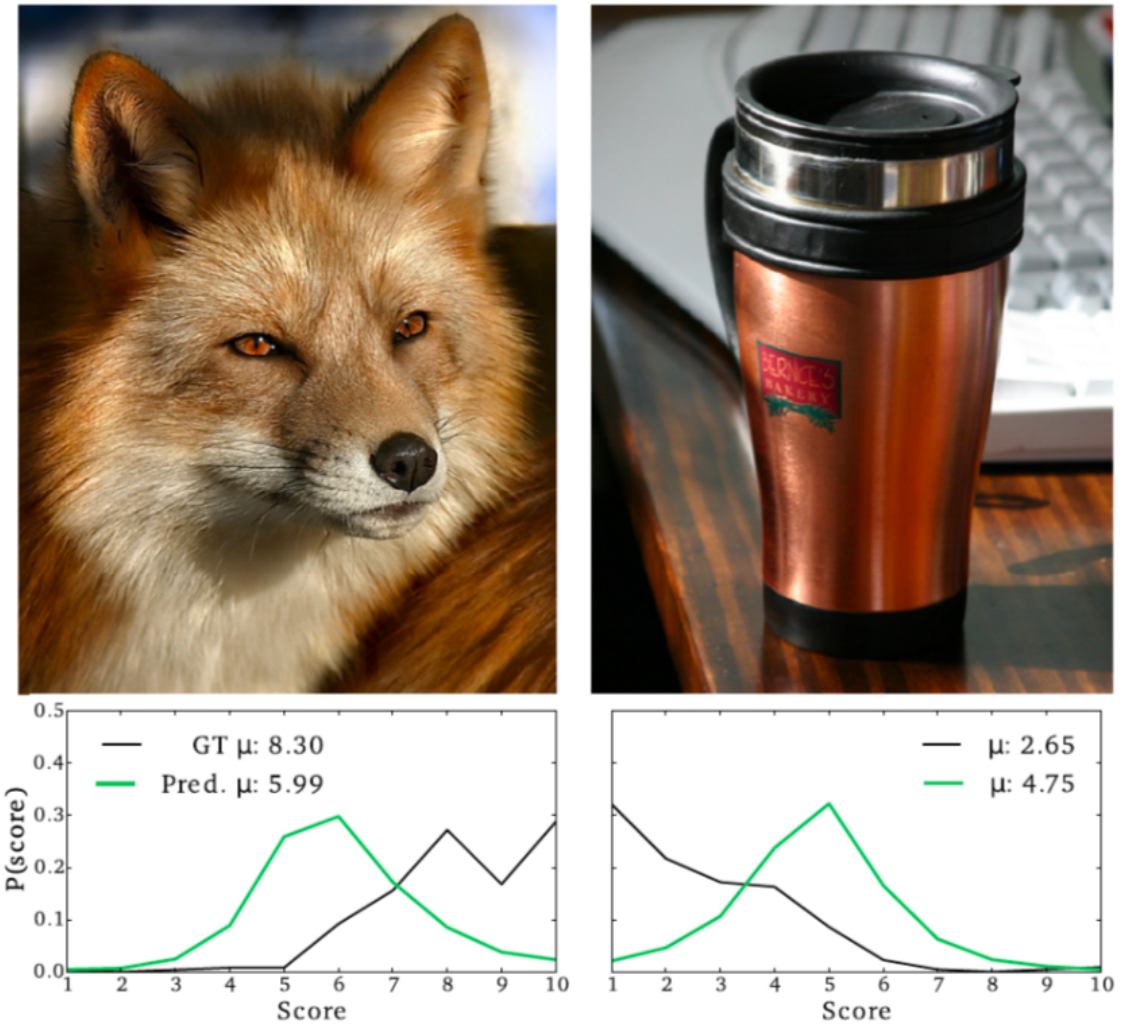
Failure cases

The model fails for images with extremely good/bad scores:



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A step towards interpretability

We want to know not just how aesthetically pleasing an image is but ***why.***

Some works visualize the learned convolutional weights in early layers

- Too low-level for aesthetics

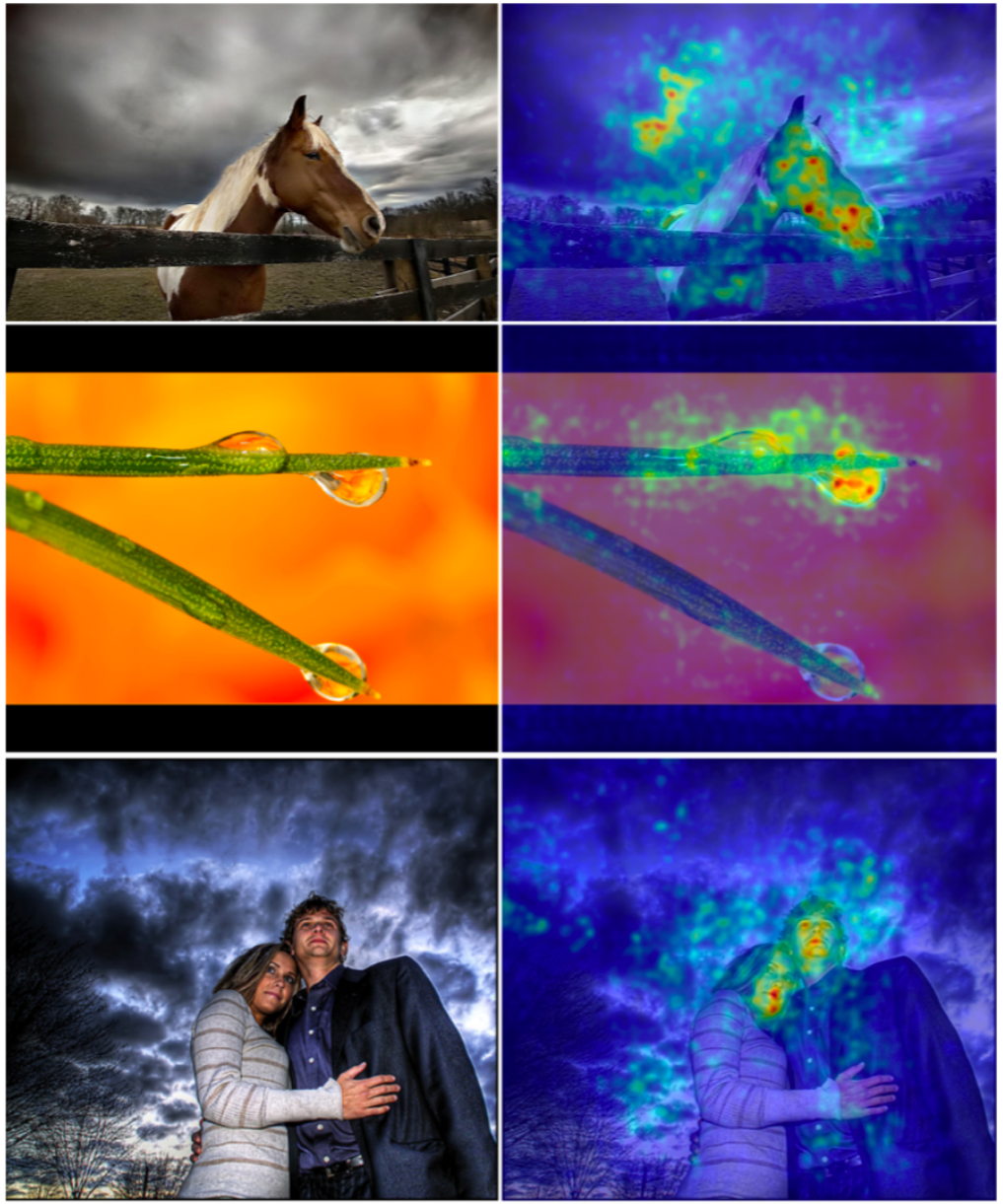
We propose an adversarial approach:

- Modify an image by gradient descent such that it has a lower/higher predicted score
- Visualize the regions that were most modified

Adversarial images & their heatmaps

Observations:

- Much easier to worsen an aesthetic score than improve it
- Most modified regions tend to contain salient objects



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From predicting to generating

Conditioning generative image models on aesthetic properties

Quite a few recent works on conditioning generative image models:

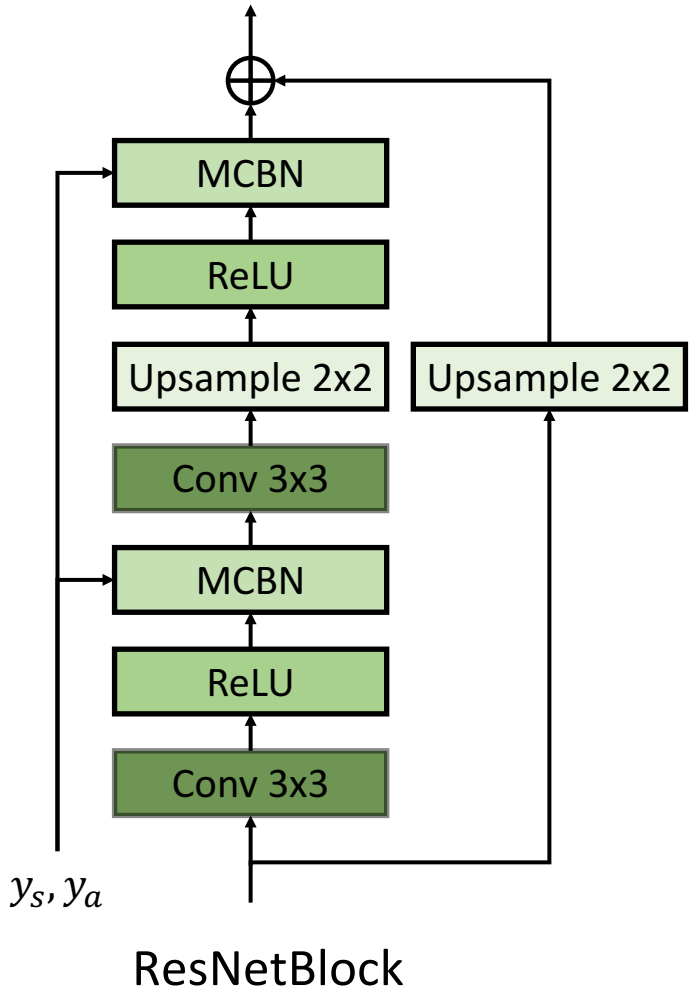
- On categorical variables [1]
- On human pose [2]
- On semantic layout [3]

We propose a GAN for photographic fine art (PFAGAN):

- The discriminator and generator are conditioned on semantics *and* aesthetics.
- We use normalized score histograms to condition on aesthetics.

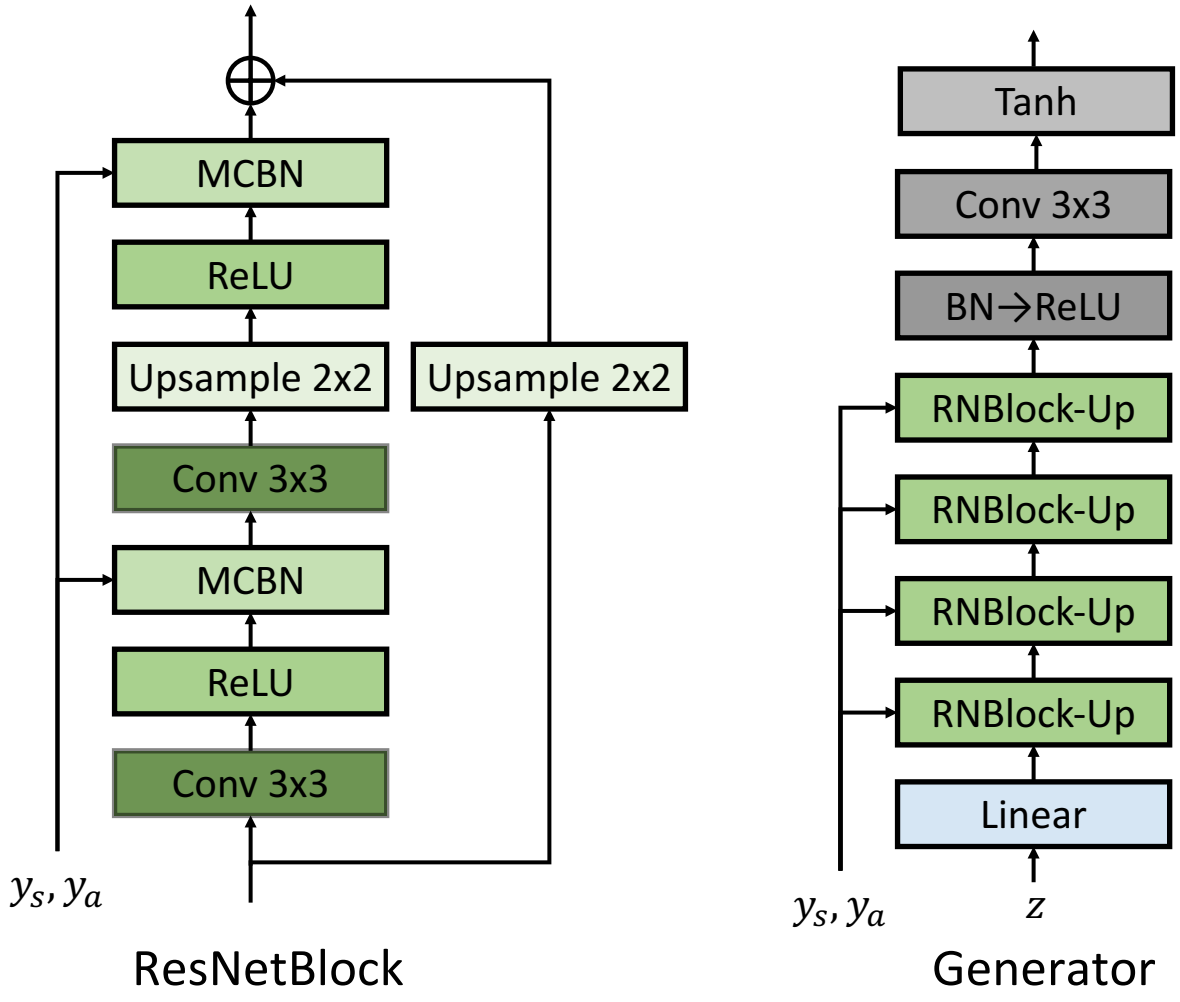
[1] Mirza & Osindero. Conditional generative adversarial nets. *arXiv*, 2014.
[2] Dong et al. Soft-Gated Warping-GAN for Pose-Guided Person Image Synthesis. NeurIPS 2018.
[3] Chen & Koltun. Photographic Image Synthesis with Cascaded Refinement Networks. ICCV 2017.

PFAGAN architecture



Murray. PFAGAN: An aesthetics-conditional GAN for generating photographic fine art. Under review.

PFAGAN architecture



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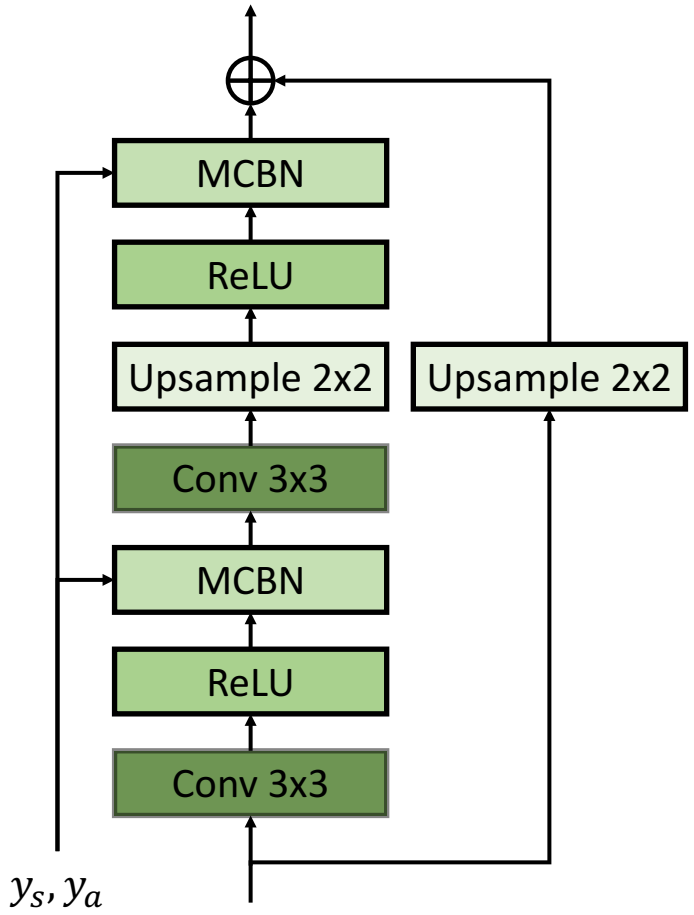
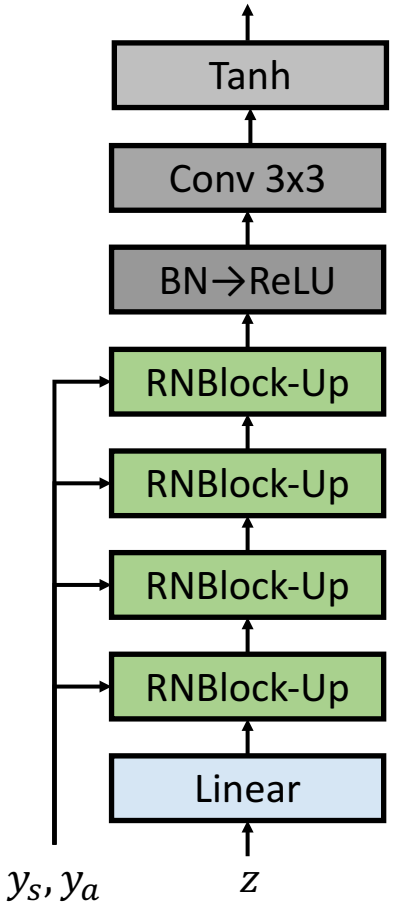
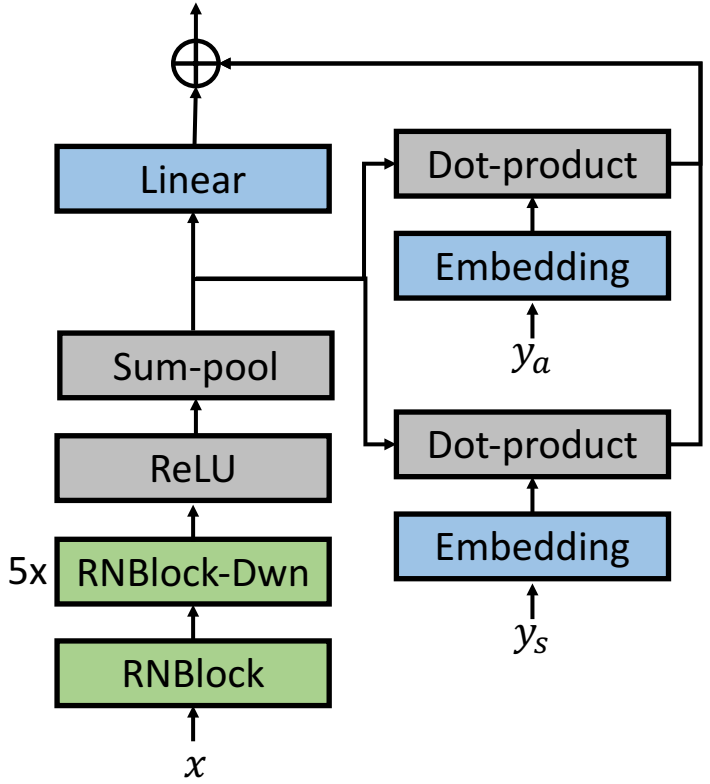
PFAGAN architecture



ResNetBlock



Generator



Discriminator

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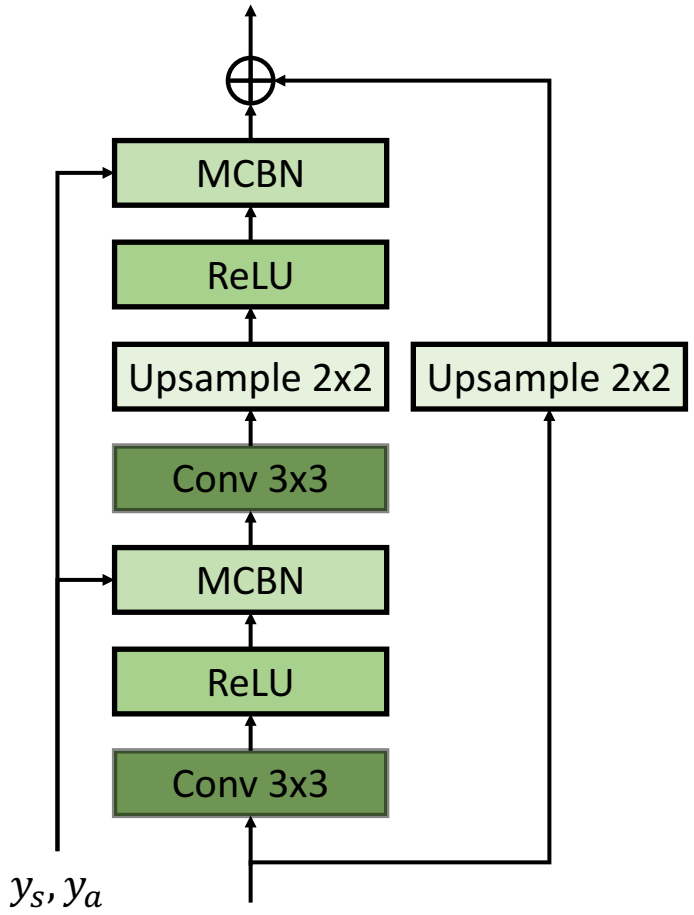
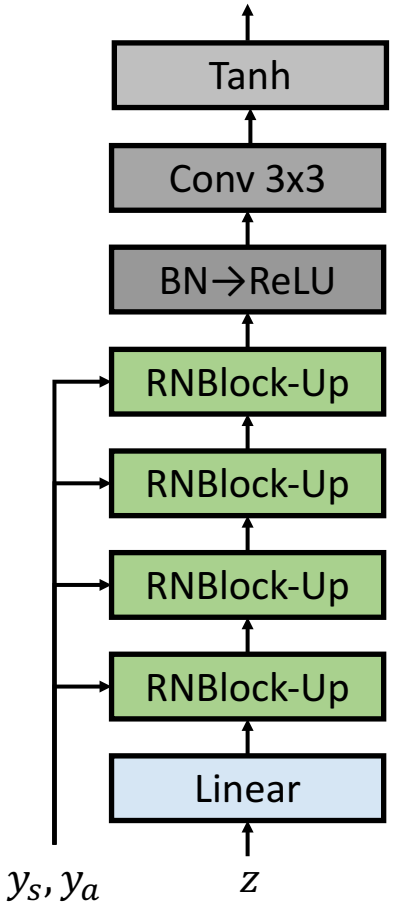
PFAGAN architecture

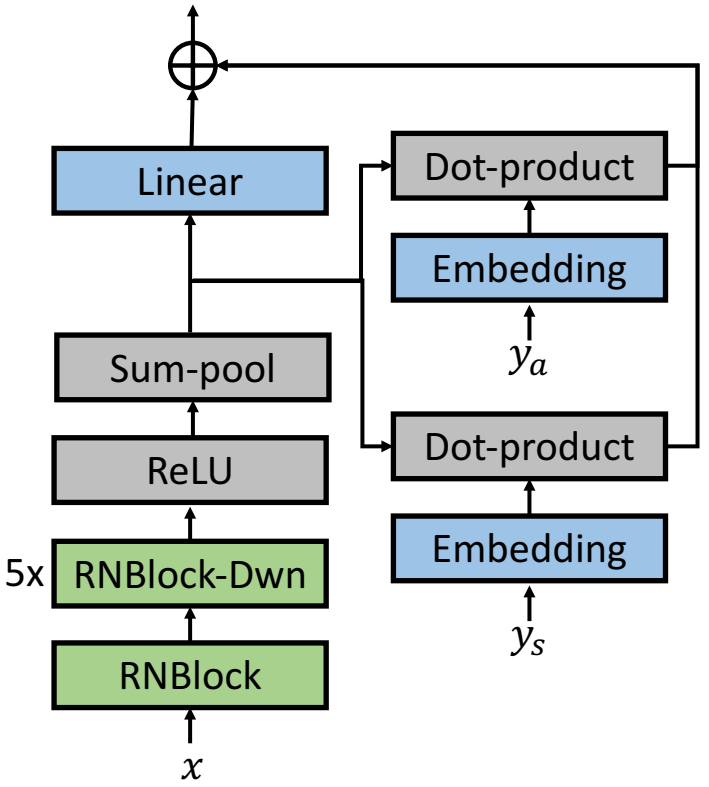


ResNetBlock



Generator

Similar architecture to Miyato & Koyama*



Discriminator

*Miyato and Koyama. cgans with projection discriminator. *ICLR*, 2018.

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Conditioning the generator

To condition the generator we propose a “mixed-conditional” BN layer:

$$o_{i,c} = \lambda_{s,a,c}\left(\frac{h_{i,c} - \mu_c}{\sigma_c}\right) + \beta_{s,a,c}$$

Where $\boldsymbol{\lambda}_{s,a}$ and $\boldsymbol{\beta}_{s,a}$ are computed using affine transformations:

$$\boldsymbol{\lambda}_{s,a} = \boldsymbol{y}'_a W_s^{\lambda} + \boldsymbol{b}_s^{\lambda}; \qquad \boldsymbol{\beta}_{s,a} = \boldsymbol{y}'_a W_s^{\beta} + \boldsymbol{b}_s^{\beta}$$

Each semantic category s is associated with two affine transforms.

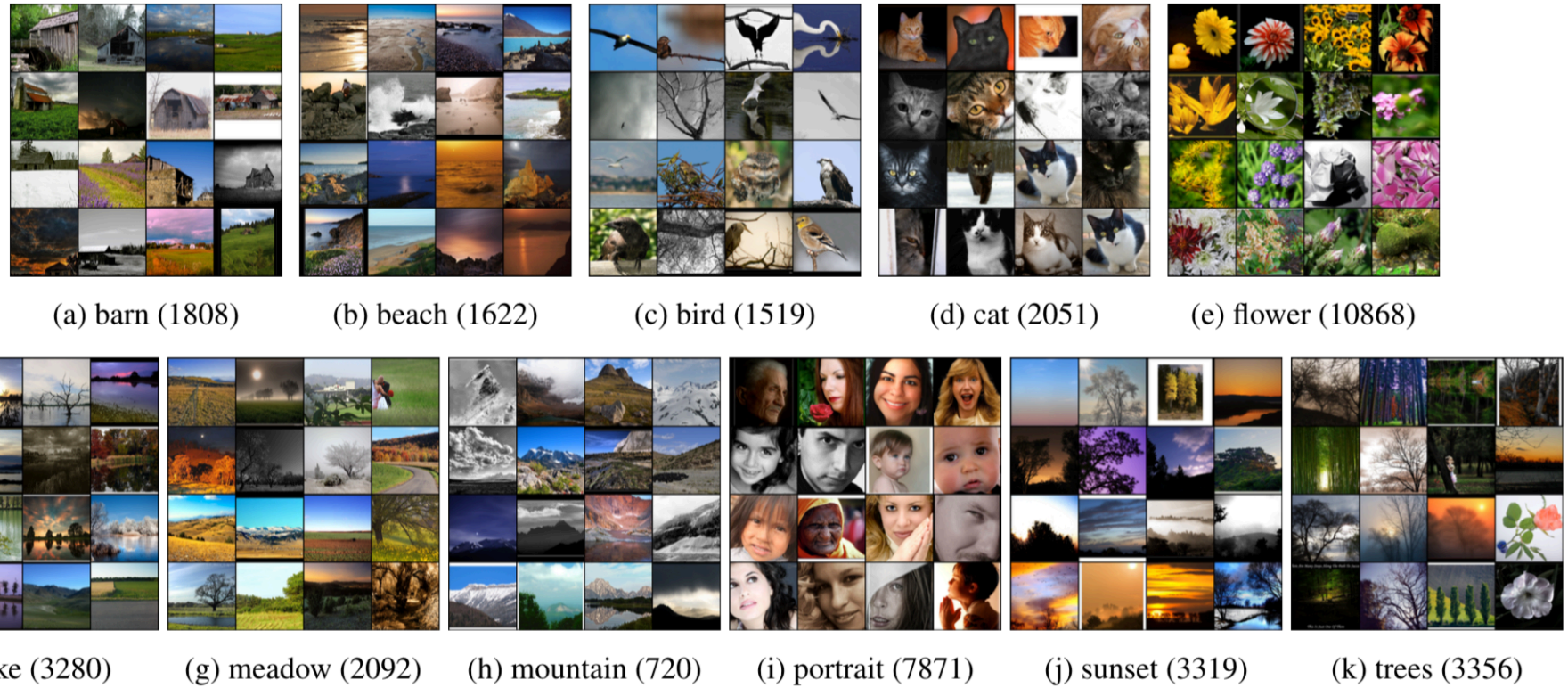
Related to both conditional batch normalization [1] and conditional instance normalization [2].

[1] De Vries et al. Modulating early visual processing by language. *NIPS*, 2017.
[2] Dumoulin and Kudlur. A learned represen tation for artistic style. *ICLR*, 2017.

Training PFAGAN with AVA

We use normalized score histograms to condition on aesthetics.

We cluster the images in AVA to obtain the following semantic categories:



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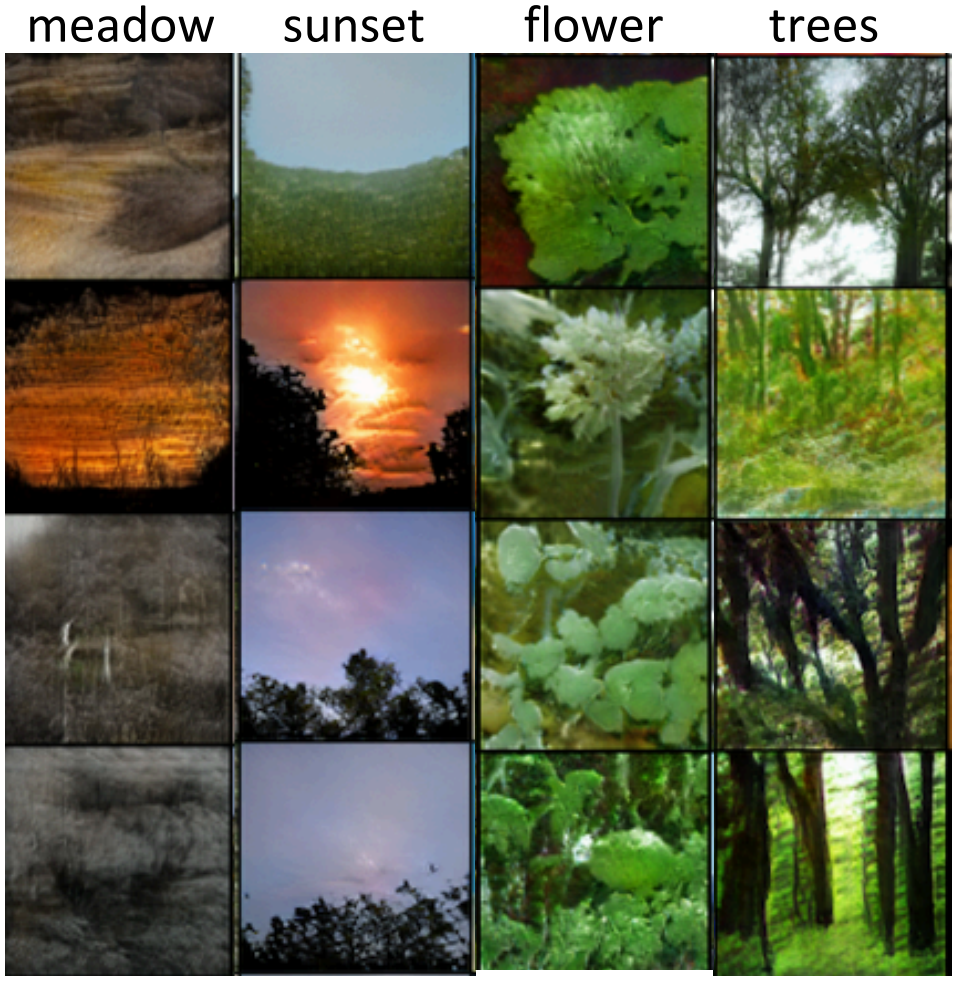
Generated samples: successful classes



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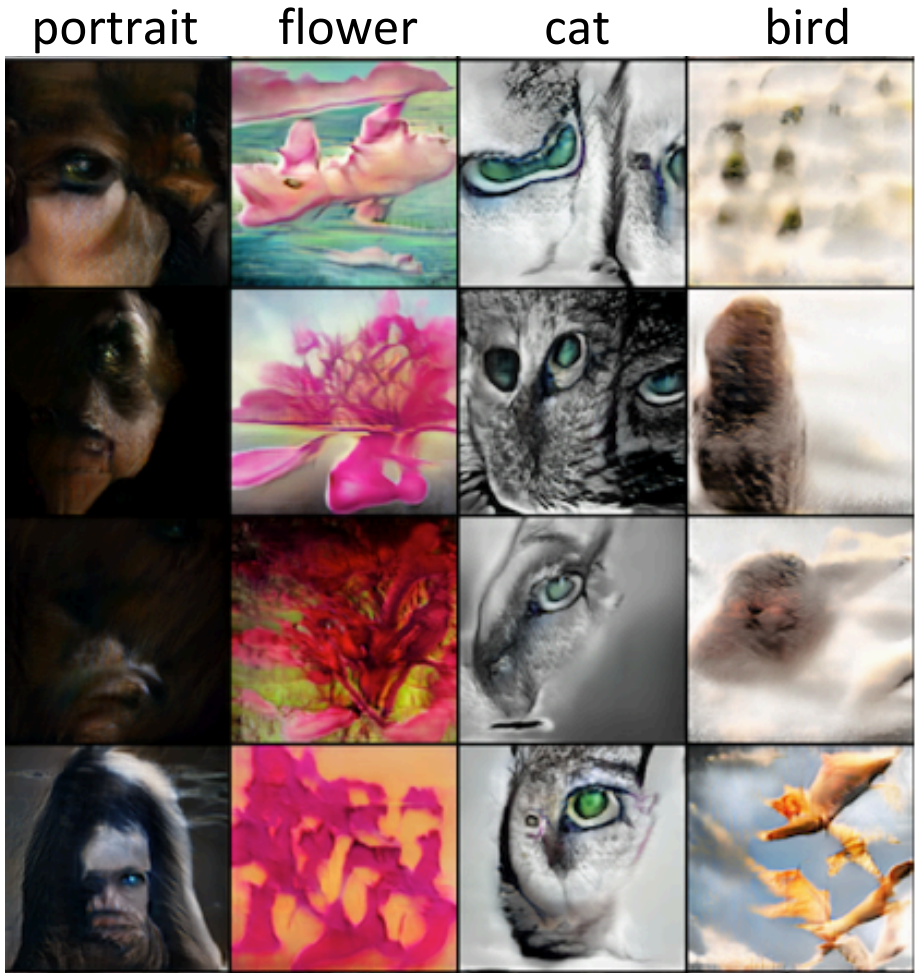
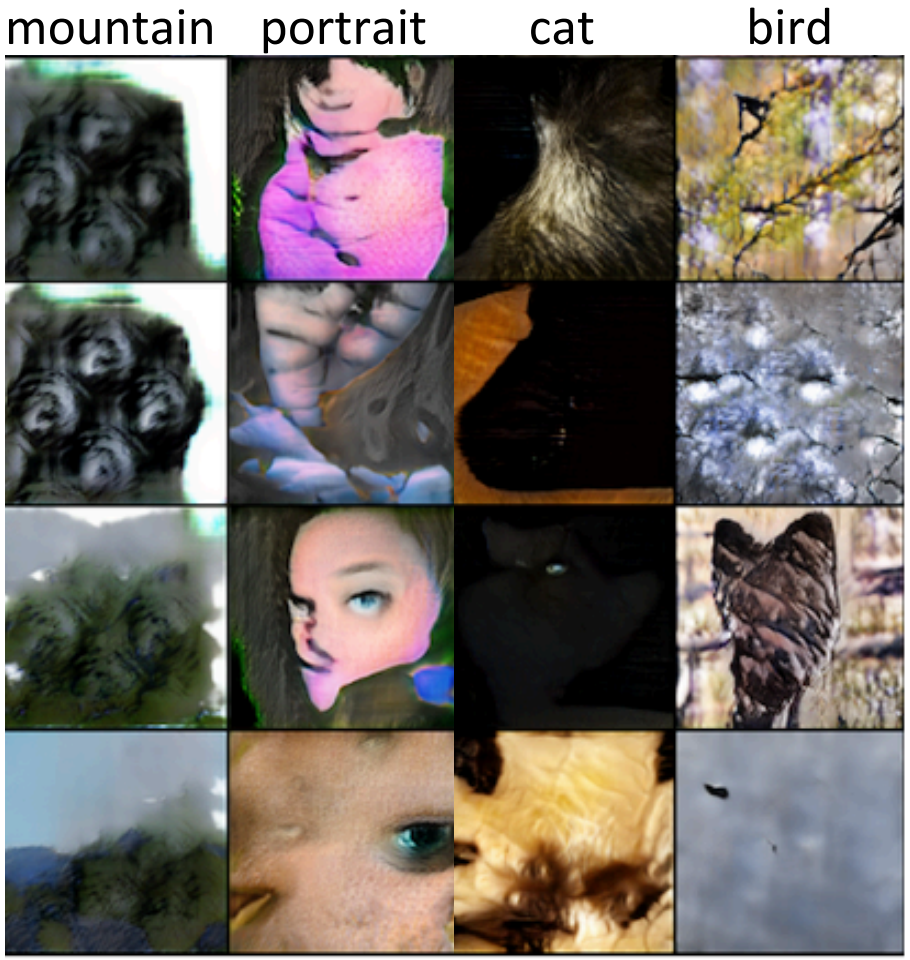
Generated samples: failure cases





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Global summary

Supervised learning of image aesthetics models is effective given:

- Large-scale datasets.
- Powerful deep image representations.

Major challenge is dataset bias:

- Most images are “average”.
- Content is biased towards a few categories (landscapes, portraits, etc.).
- Raters are self-selected and participation is unbalanced.

Thank you!