

Using Deep Learning to rank and tag millions of hotel images

15/11/2018 - PyParis 2018

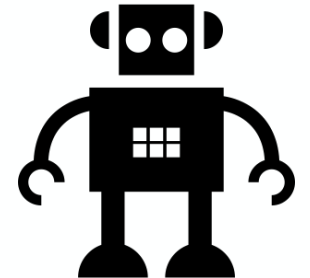
Christopher Lennan (Senior Data Scientist)
@chris_lennan

Tanuj Jain (Data Scientist)
@tjainn

#idealoTech

Agenda

1. idealo.de
2. Business Motivation
3. Models and Training
4. Image Tagging
5. Image Aesthetics
6. Summary



Some Key Facts



More than 18 years experience



Germany's 4th largest eCommerce website



Active in 6 different countries (DE, AT, ES, IT, FR, UK)



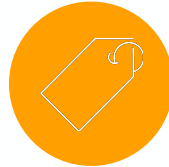
700 "idealos" from 40 nations



16 million users/month ¹



50.000 shops



Over 330 million offers for 2 million products



Tüv certified comparison portal ²

Motivation



idealo hotel price comparison

hotel.ideal.de



← → ↻ 🔒 <https://hotel.ideal.de/unterkuenfte/Berlin-s2950159/>

↓ Wissenswertes zum Reiseziel

idealo.de > Hotel-Preisvergleich > Deutschland > Unterkunftssuche Berlin

Unterkunft-Preis pro Nacht filtern:
13 € ————— 2614 €

Hotel-Sterne filtern

- ★★★★★
- ★★★★
- ★★★
- ★★
- ★

Unterkunft-Bewertung filtern:

- ab 8,5 Pkt. - "Exzellent"
- ab 8,0 Pkt. - "Super"
- ab 7,5 Pkt. - "Sehr Gut"
- ab 6,9 Pkt. - "Gut"
- ab 6,0 Pkt. - "OK"


Lage

- Zentrum 1130
- Strandnah 2


Unterkunftsarten Berlin

- Alle Unterkunftsarten
- Ferienwohnungen


2835 Unterkünfte in Berlin ab 13 €* Sortierung: Beliebtheit



★★★★★
Leonardo Royal Hotel Berlin Alexanderpl...
8,6 Exzellent
pro Nacht, Ø ab **74 €**
⊙ 0,9 km Stadtzentrum [Karte](#)
Spa | Bio-Hotel | Sauna | WLAN
[Infos](#) [Verfügbarkeit prüfen](#) [zum Angebot](#) bei Elviline



★★★★
Hotel Amano
8,6 Exzellent
pro Nacht, Ø ab **86 €**
⊙ 0,7 km Stadtzentrum [in Karte anzeigen](#)
Spa | Pool | Design | WLAN
[Infos](#) [Verfügbarkeit prüfen](#) [zum Angebot](#) bei Booking.com



★★★★★
Melia Berlin
9 Exzellent
pro Nacht, Ø ab **108 €**
⊙ 1,6 km Stadtzentrum [Karte](#)
Wellness | Familie | Sauna | WLAN
[Infos](#) [Verfügbarkeit prüfen](#) [zum Angebot](#) bei Roomdi

- 2.306.658 accommodations
- 308.519.299 images
- ~ 133 images per accommodation

Importance of Photography for Hotels

“.. after price, photography is the most important factor for travelers and prospects scanning OTA sites..”

“.. Photography plays a role of 60% in the decision to book with a particular hotel ..”

“.. study published today by **TripAdvisor**, it would seem like **photos have the greatest impact** driving engagement from travelers **researching on hotel and B&B pages** ..”

mehr ▾

Geprüft von **idealo**

- Wellness
- Familien
- Umweltfreundliche
- Romantische
- Luxus
- Design


Allgemeine Ausstattungsfiler

- WLAN
- Pool
- Parkplatz
- Fitnessraum
- Restaurant
- Nichtraucherzimmer
- Shuttle Service
- Klimaanlage

mehr ▾

Ambiente

- Business



★★

Hotel Comenius

8,5 Super

pro Nacht, Ø


ab **44 €**

📍 3,0 km Stadtzentrum [Karte](#)

Spa | Sauna | WLAN | Fitnessraum

[Infos ▾](#) [Verfügbarkeit prüfen](#)

zum Angebot >
bei Booking.com



★

Heart of Gold Hostel Berlin

8,4 Super

pro Nacht, Ø


ab **31 €**

📍 1,3 km Stadtzentrum [Karte](#)

WLAN | Klimaanlage | Spielzimmer | Fahrrad...

[Infos ▾](#) [Verfügbarkeit prüfen](#)

zum Angebot >
bei Booking.com



★

Cityhostel Berlin

8,1 Super

pro Nacht, Ø

ab **36 €**

📍 2,2 km Stadtzentrum [Karte](#)

WLAN | Spielzimmer | Fahrradverleih | Toura...

[Infos ▾](#) [Verfügbarkeit prüfen](#)

zum Angebot >
bei HRS



★★

Hotel Comenius

8,5 Super

📍 3,0 km Stadtzentrum [Karte](#)

Spa | Sauna | WLAN | Fitnessraum

[Infos](#) ▾

[Verfügbarkeit prüfen](#)

pro Nacht, Ø

ab **44 €**

[zum Angebot](#) >
bei Booking.com



★★

Hotel Comenius

8,5 Super

pro Nacht, Ø

ab **44 €**

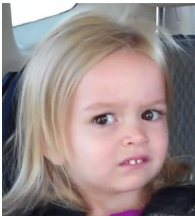
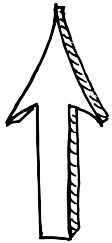
📍 3,0 km Stadtzentrum [Karte](#)

Spa | Sauna | WLAN | Fitnessraum

[Infos](#) ▾

[Verfügbarkeit prüfen](#)

[zum Angebot](#) >
bei Booking.com



1



2



3



4



5



6



7



8



9



10



11



12



13



Image Aesthetics

Current image placement

Position: 1



Position: 19



Image Aesthetics

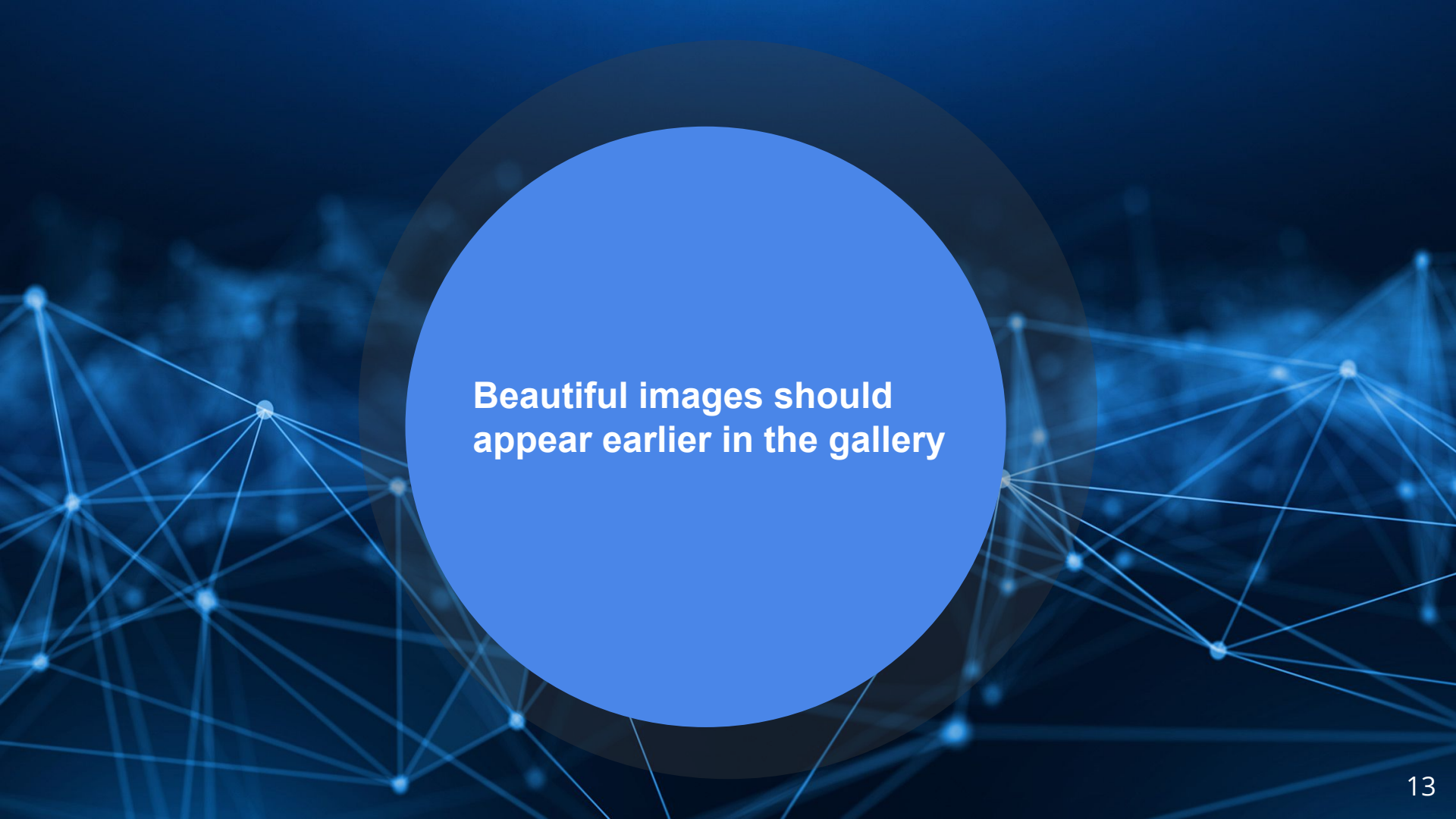
Current image placement

Position: 3



Position: 17





**Beautiful images should
appear earlier in the gallery**

1



2



3



4



5



6



7



8



9



10



11



12



13



1



2



3



4



5



6



7



8



9



10



11



12



13





Ensure different areas get depicted

Bedroom

1



2



3



Bathroom

4



Restaurant

5



Facade

6



Fitness Studio

7



Kitchen

8



Understanding Image Content

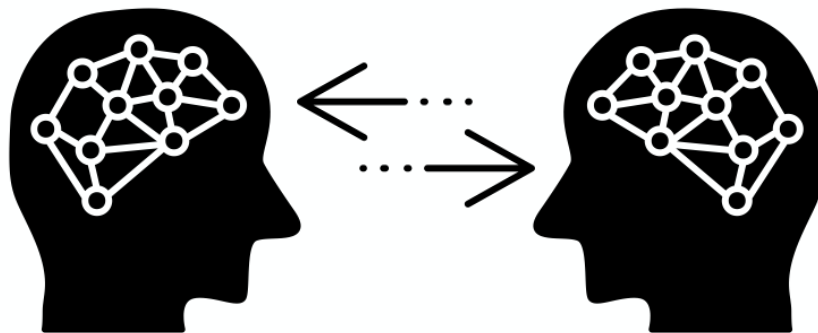
Two part problem

1. Tag the image with the hotel property area
2. Predict aesthetic quality

Models & Training

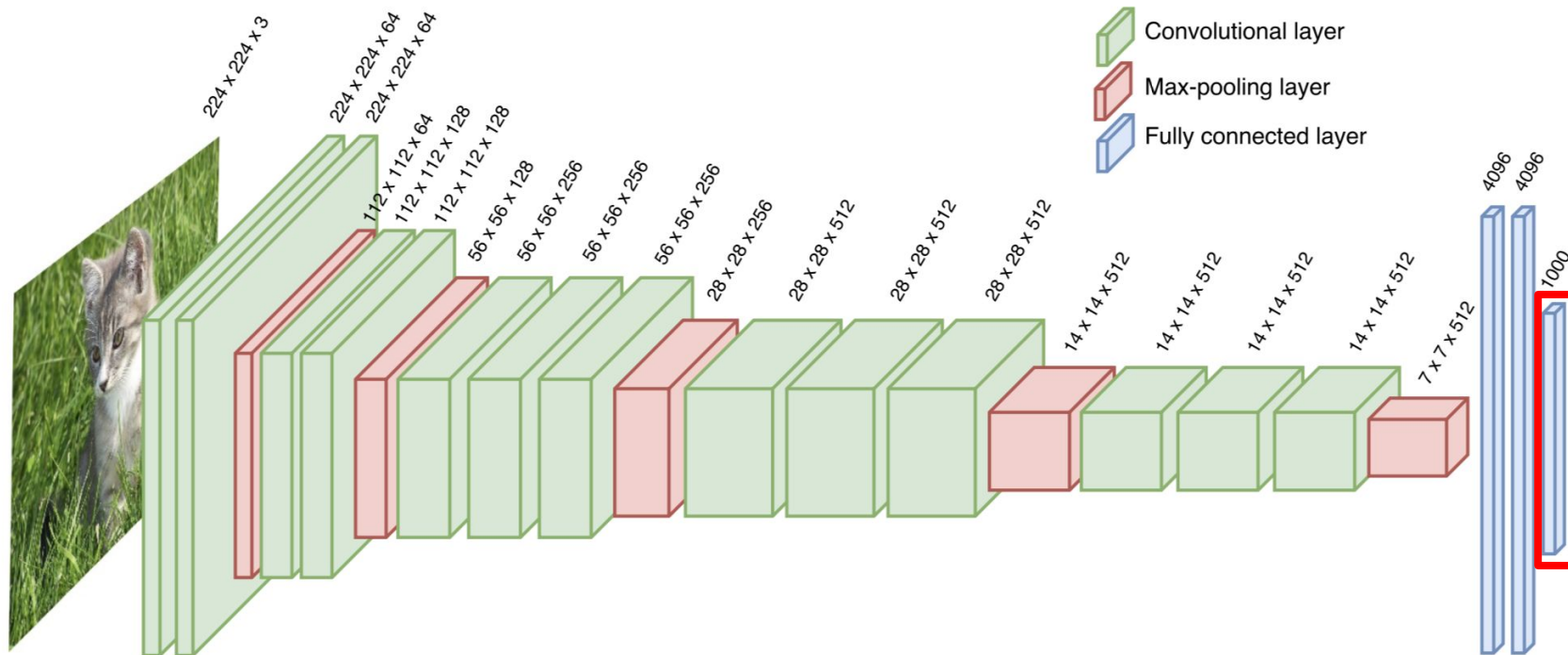
Transfer Learning

- Use pre-trained CNN that was trained on millions of images (e.g. MobileNet or VGG16)
- Replace top layers so that the output fits with classification task
- Train existing and new layer weights



Transfer Learning

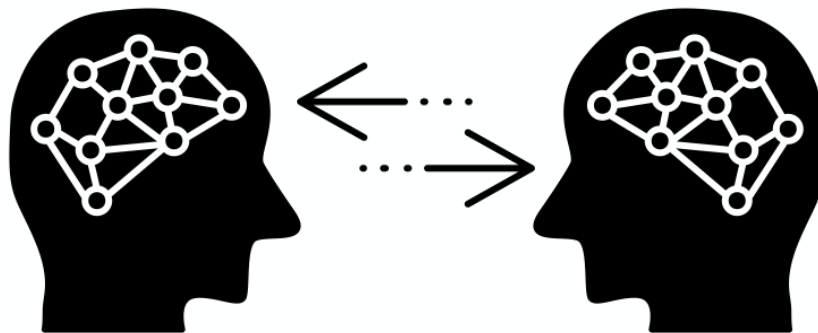
CNN architecture (VGG16)

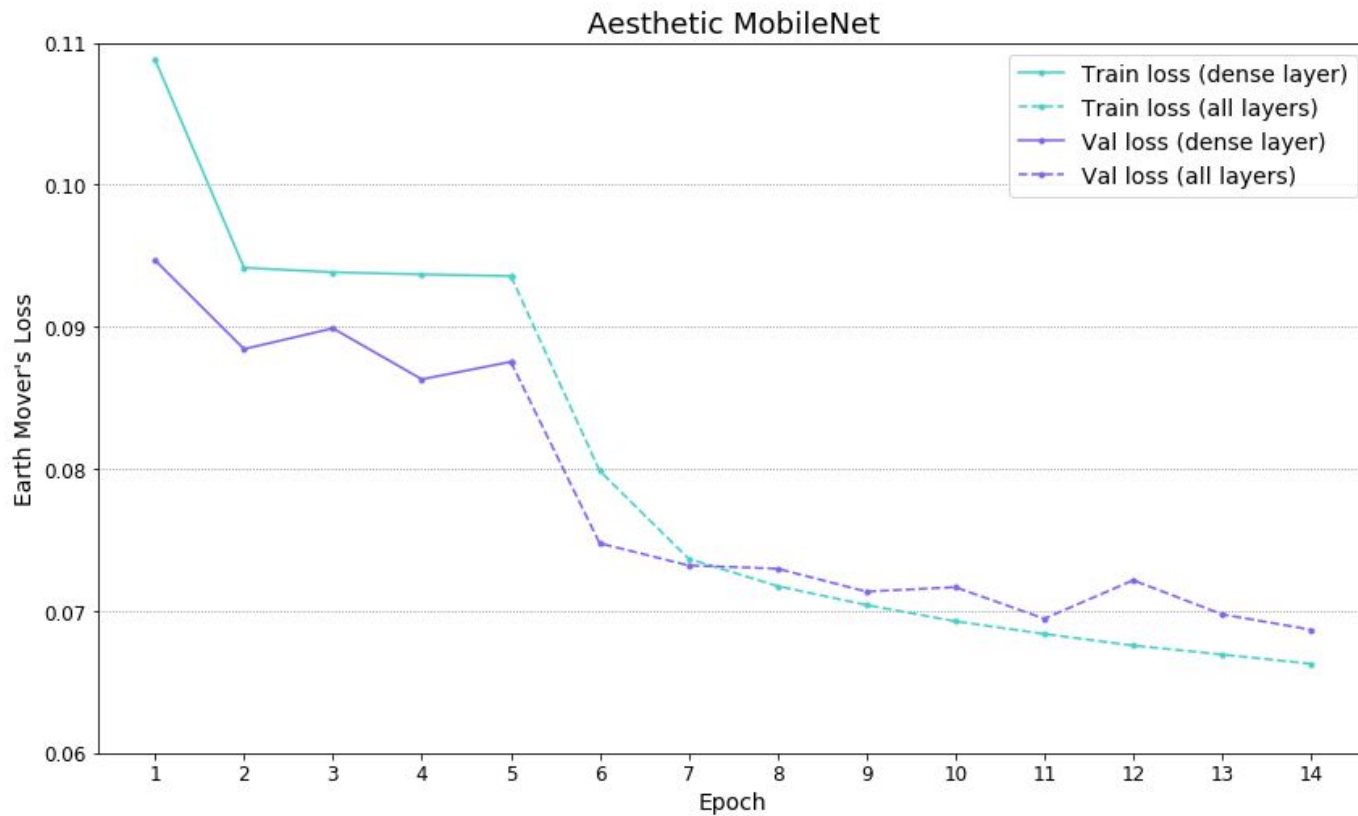


Training regime

1. Only train the newly added dense layers with high learning rate
2. Then train all layers with low learning rate

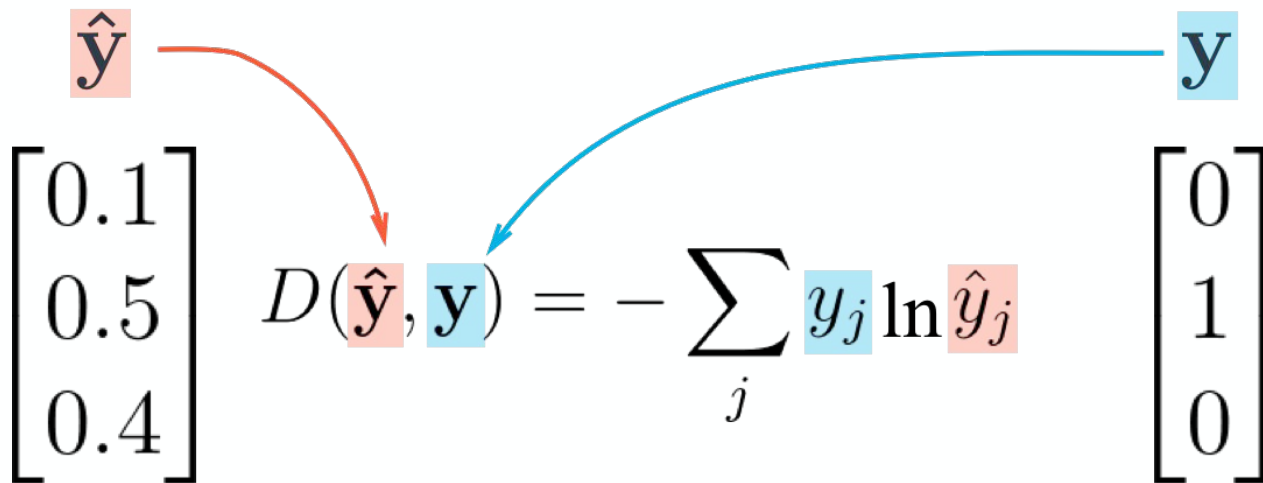
Goal: Do not juggle around the pre-trained convolutional weights too much





Cross-entropy loss (CEL)

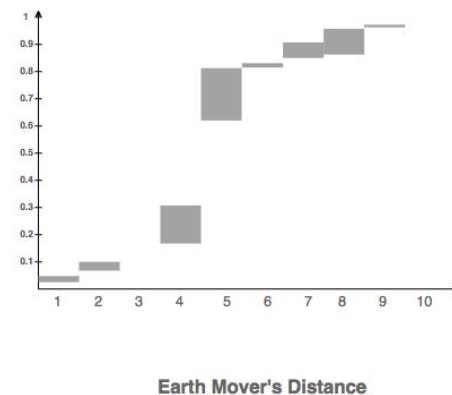
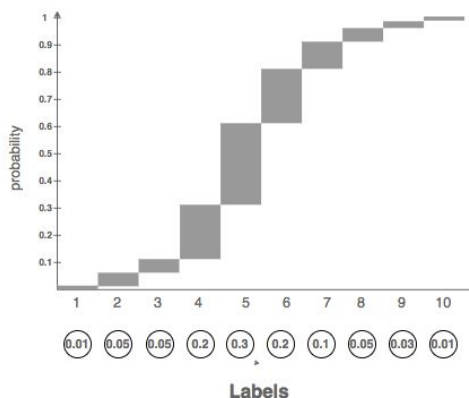
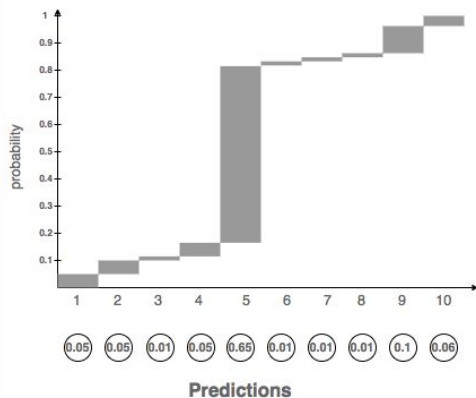
- CEL generally used for “one-class” ground truth classifications (e.g. image tagging)
- CEL ignores inter-class relationships between score buckets


$$D(\hat{\mathbf{y}}, \mathbf{y}) = - \sum_j y_j \ln \hat{y}_j$$

Loss functions

Earth Mover's Distance (EMD)

- For ordered classes, classification settings can outperform regressions
- Training on datasets with intrinsic ordering can benefit from EMD loss objective



GPU training workflow

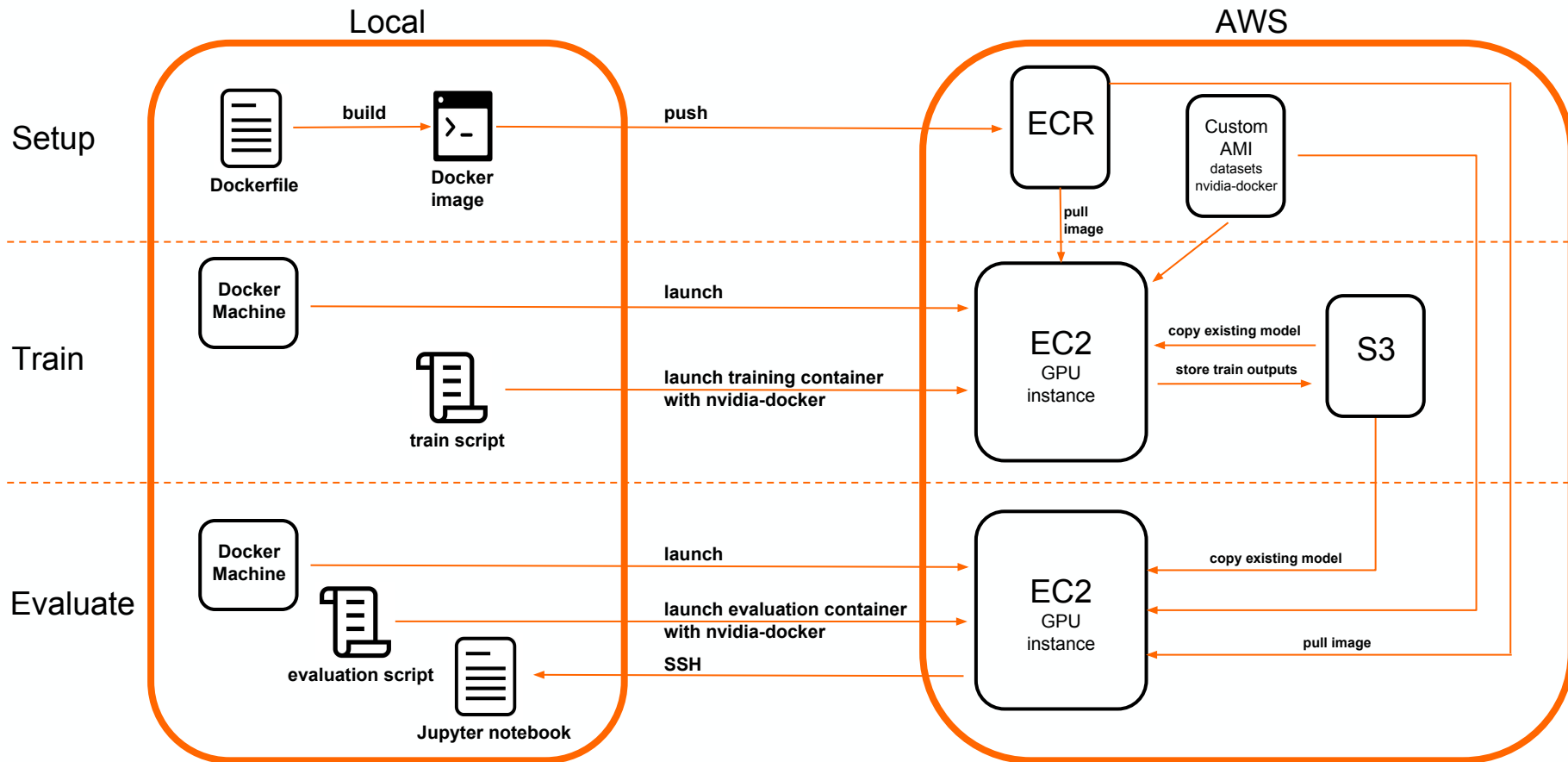


Image Tagging



- Given an image, tag it as belonging to a **single** class

- Multiclass classification model with classes:
 - Bedroom
 - Bathroom
 - Foyer
 - Restaurant
 - Swimming Pool
 - Kitchen
 - View of Exterior (Facade)
 - Reception

Multiple Datasets

Will go over them one-by-one and see:

- Dataset properties
- Results
- Issues

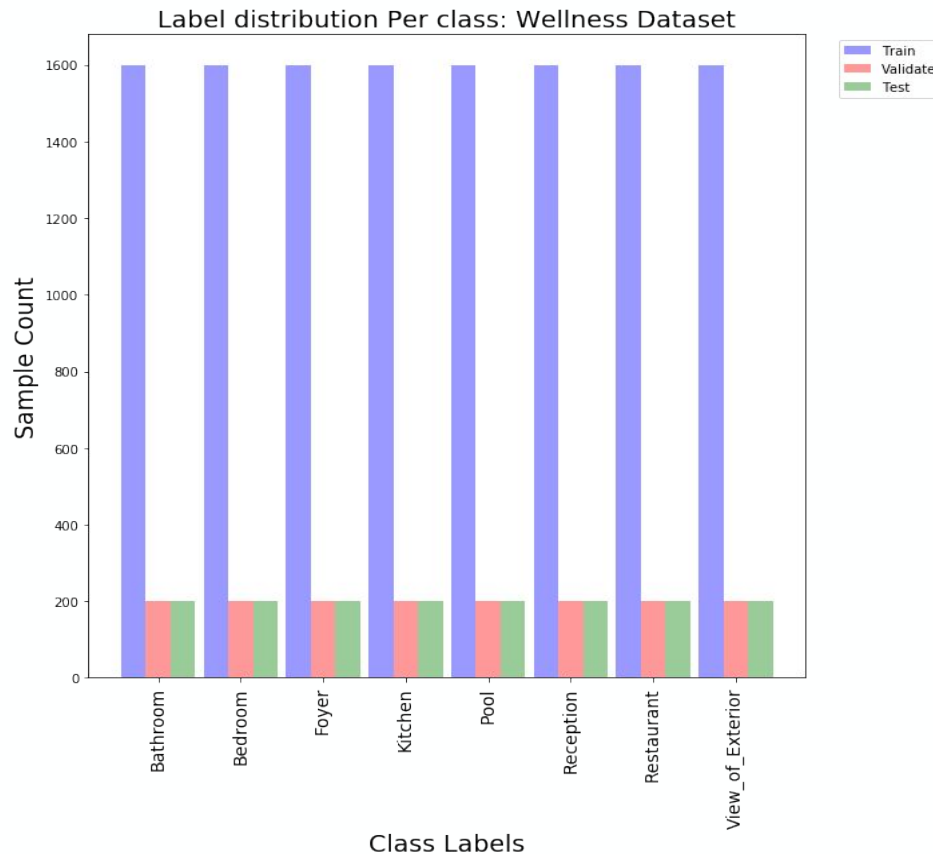
Wellness Dataset

- Idealo in-house **pre-labelled** images
- Mostly pictures of 2 or 3 stars properties



Wellness Dataset

- Balanced: Equal sample count in all categories for all sets



Wellness Dataset: Metrics

Top-1- accuracy: 86%

	precision	recall	f1-score	support
0	0.97	0.89	0.92	200
1	0.85	0.90	0.87	200
2	0.74	0.74	0.74	200
3	0.85	0.94	0.89	200
4	0.89	0.98	0.94	200
5	0.76	0.86	0.81	200
6	0.91	0.80	0.85	200
7	0.98	0.81	0.89	200
avg / total	0.87	0.86	0.86	1600

	Bathroom	Bedroom	Foyer	Kitchen	Pool	Reception	Restaurant	View_of_Exterior
Bathroom	177	4	2	8	0	9	0	0
Bedroom	1	180	17	1	0	1	0	0
Foyer	3	24	149	2	0	19	2	1
Kitchen	0	1	2	187	0	8	2	0
Pool	0	0	1	0	196	0	3	0
Reception	0	1	8	16	0	172	3	0
Restaurant	2	2	12	5	7	10	160	2
View_of_Exterior	0	1	10	0	16	6	5	162

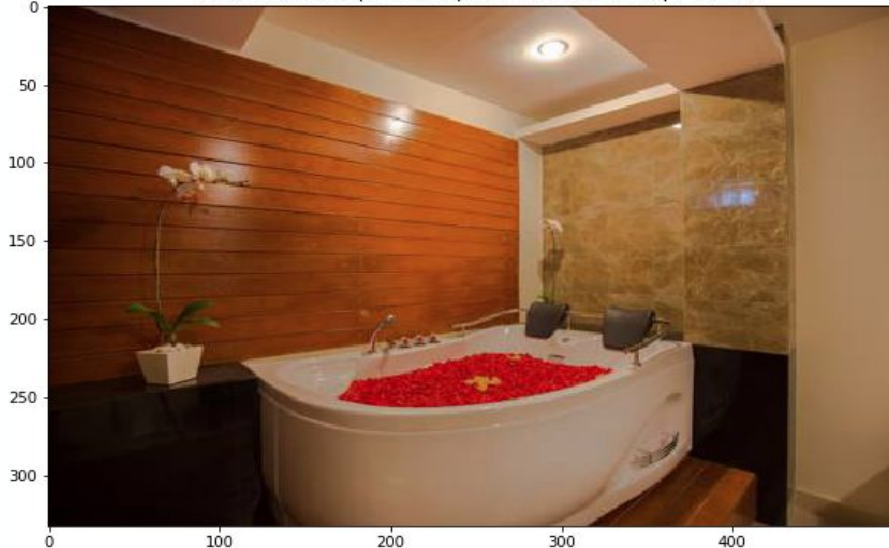
Wellness Dataset: Wrong Predictions

True Class of these images: BATHROOM, Predicted as: RECEPTION

Predicted as Reception with prob: 0.94, True class prob: 0.06



Predicted as Reception with prob: 0.81, True class prob: 0.18



Rectangular structure = Reception with high probability
→ **BIAS!**

Wellness Dataset: Wrong Predictions

True Class of these images: BATHROOM

Predicted as Bedroom with prob: 0.78, True class prob: 0.21



Predicted as Kitchen with prob: 1.00, True class prob: 0.00



Wrong true label of images
→ **NOISE** in the dataset!

- **Augmentation** operations, same for every class:
 - Random cropping
 - Rotation
 - Horizontal flipping

- **Data enrichment:**
 - External data from google images

Augmented Wellness + Google Dataset: Metrics

Top-1- accuracy: 88%

	precision	recall	f1-score	support
0	0.97	0.93	0.95	244
1	0.87	0.93	0.90	241
2	0.88	0.67	0.76	258
3	0.93	0.89	0.91	277
4	0.97	0.93	0.95	283
5	0.71	0.94	0.81	250
6	0.91	0.82	0.86	268
7	0.87	0.94	0.90	281
avg / total	0.89	0.88	0.88	2102

	Bathroom	Bedroom	Foyer	Kitchen	Pool	Reception	Restaurant	View_of_Exterior
Bathroom	227	2	0	9	0	6	0	0
Bedroom	1	225	5	1	0	7	0	2
Foyer	4	22	173	1	0	40	8	10
Kitchen	2	0	2	246	0	21	6	0
Pool	0	0	1	0	264	0	4	14
Reception	0	3	6	5	0	234	2	0
Restaurant	1	4	5	2	3	19	220	14
View_of_Exterior	0	2	4	0	5	2	3	265

Gotta Clean!



- Hand-cleaned each category:
 - Deleted pictures that do not belong in its category
 - Removed duplicates (presence of duplicates can give us wrong metrics)
 - Added more images from external sources for classes with a small number of images left after cleaning

Cleaned Data: Metrics

Top-1- accuracy: 91%

	precision	recall	f1-score	support
0	0.98	0.95	0.97	170
1	0.95	0.95	0.95	176
2	0.86	0.75	0.80	159
3	0.86	0.97	0.92	189
4	0.93	1.00	0.96	185
5	0.77	0.79	0.78	105
6	0.91	0.94	0.92	167
7	1.00	0.85	0.92	145
avg / total	0.91	0.91	0.91	1296

	Bathroom	Bedroom	Foyer	Kitchen	Pool	Reception	Restaurant	View_of_Exterior
Bathroom	162	0	0	7	0	1	0	0
Bedroom	2	168	1	4	0	1	0	0
Foyer	1	5	119	6	0	16	12	0
Kitchen	0	0	1	184	0	2	2	0
Pool	0	0	0	0	185	0	0	0
Reception	0	2	11	9	0	83	0	0
Restaurant	0	1	2	3	2	2	157	0
View_of_Exterior	0	0	4	0	13	3	2	123

Cleaned Dataset: Results

- Bathroom vs. Reception confusion has almost vanished!
- View_of_exterior vs Pool confusion has reduced
- Foyer performance:
 - Most misclassifications of Foyer gets assigned to Reception
 - This is human problem as well!

Foyer or Reception?



Learnings so far

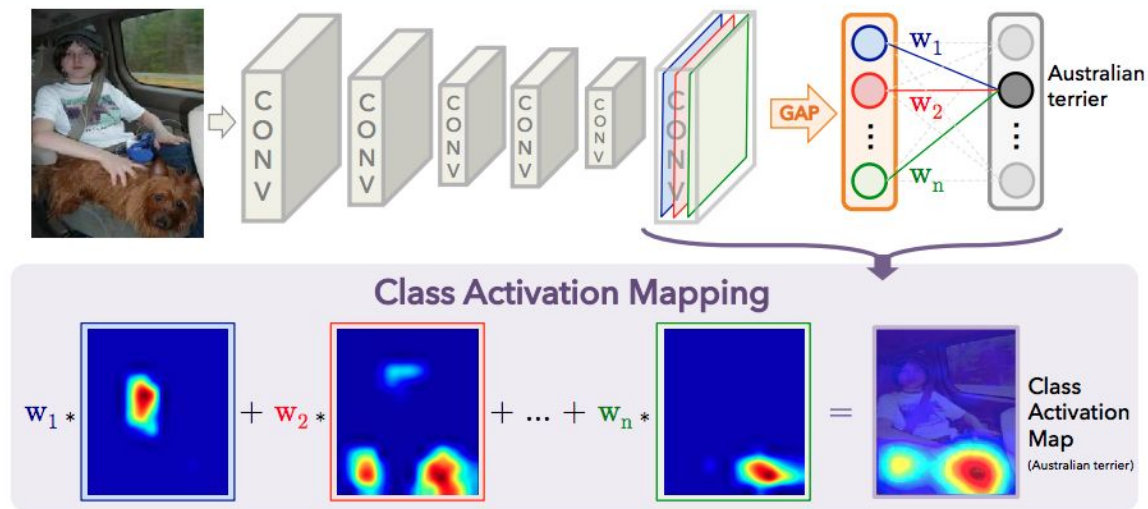
- The model can only be as good as the data (cleaning)
- Foyer is a hard category to predict

Understanding Model Decisions



Understanding Decisions: Class Activation Maps

- Use the penultimate Global Average Pooling Layer (GAP) to get class activation map
- Highlights discriminative region that lead to a classification

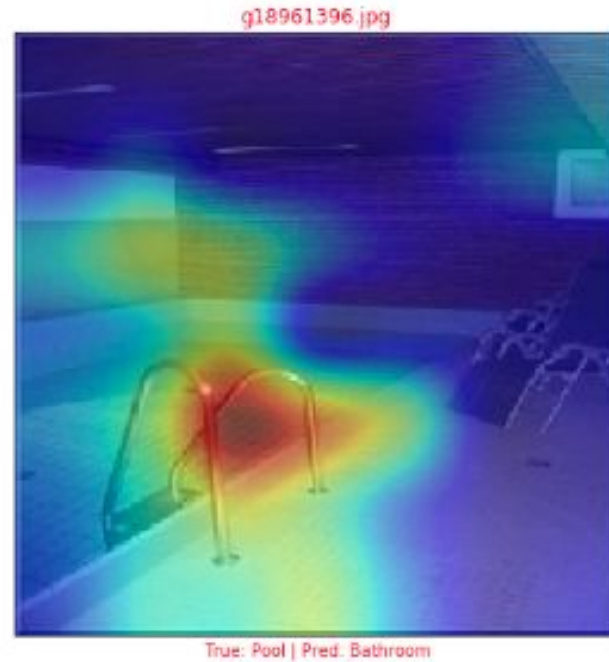


Insights With CAM

Swimming Pool misclassified as Bathroom

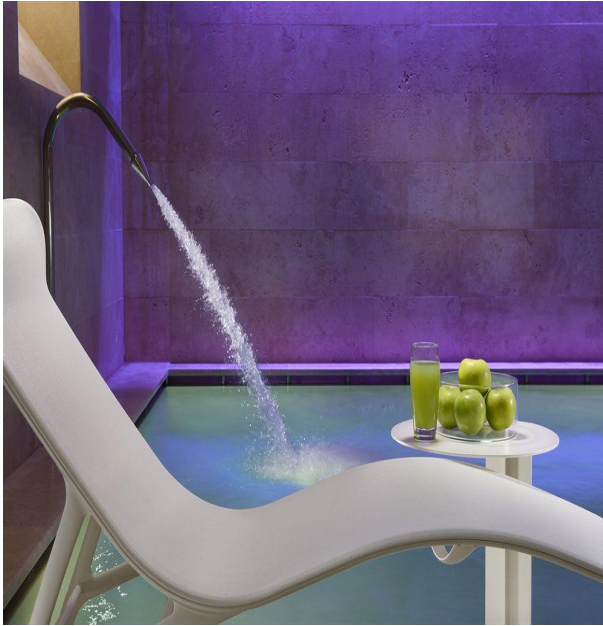


CAM

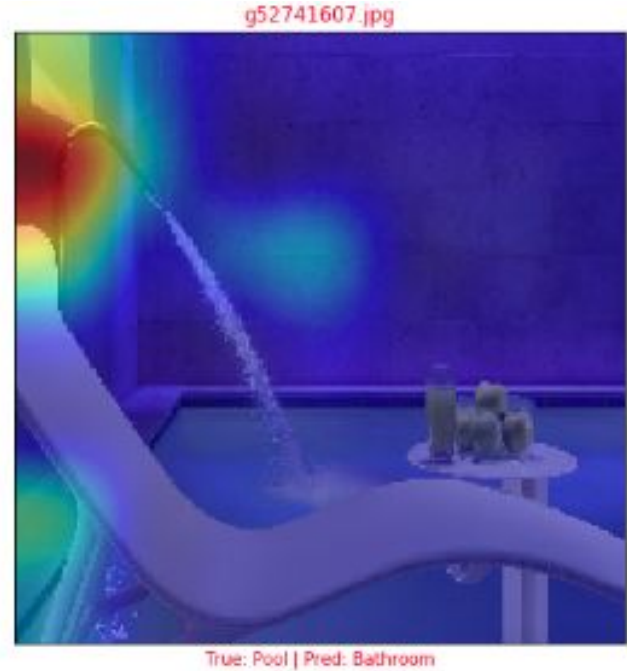


Insights With CAM

Swimming Pool misclassified as Bathroom



CAM

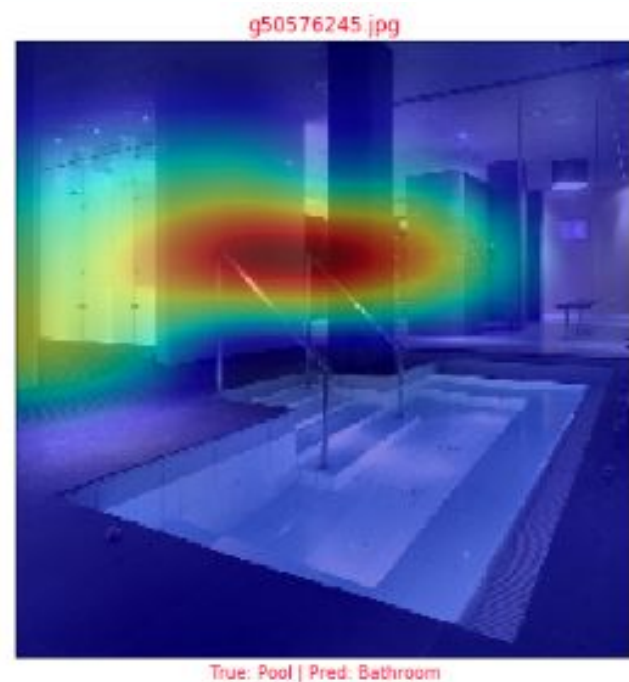


Insights With CAM

Swimming Pool misclassified as Bathroom



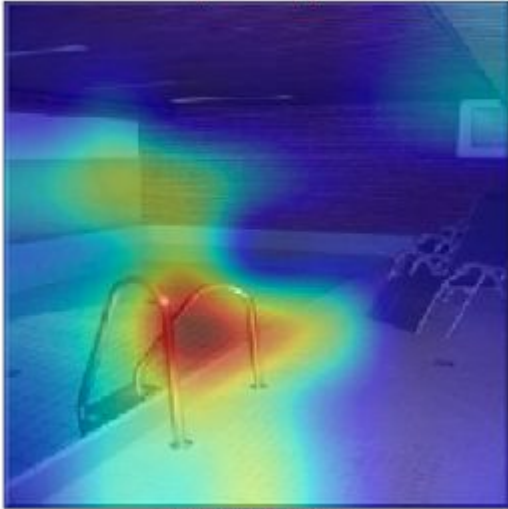
CAM



Insights With CAM

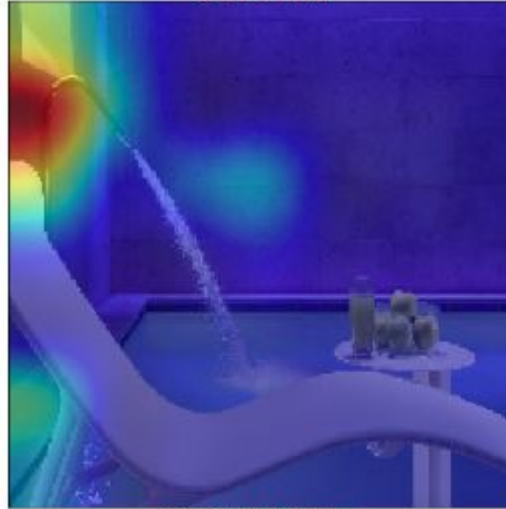
Swimming Pool misclassified as Bathroom

g18961396.jpg



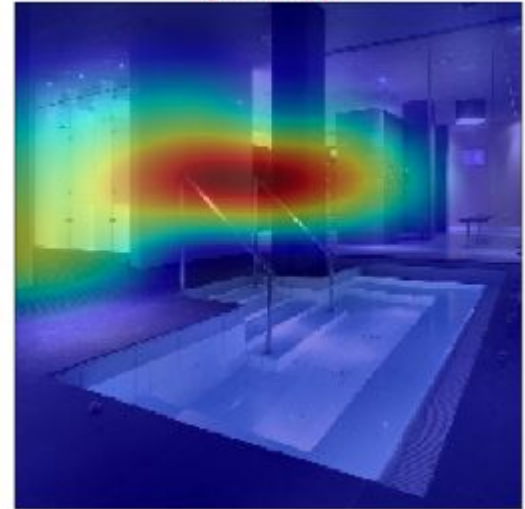
True: Pool | Pred: Bathroom

g52741607.jpg



True: Pool | Pred: Bathroom

g50576245.jpg



True: Pool | Pred: Bathroom



Using rails to misidentify Pool as Bathroom.

Insights With CAM

Bathroom correct classification



CAM

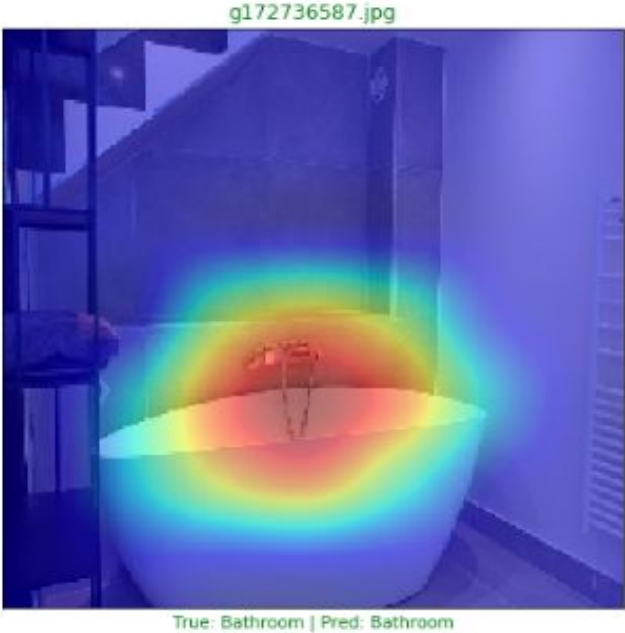


Insights With CAM

Bathroom correct classification



CAM



Insights With CAM

Bathroom correct classification



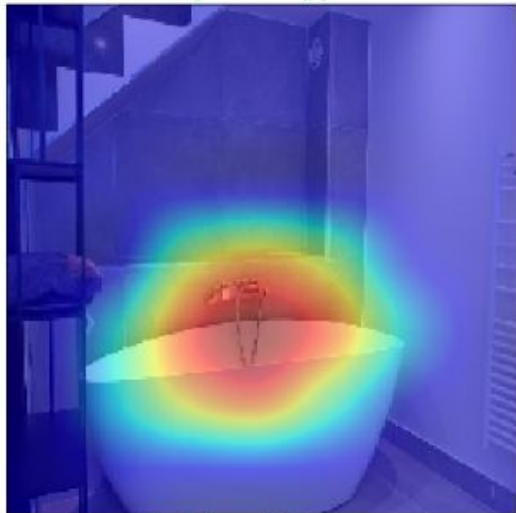
CAM



Insights With CAM

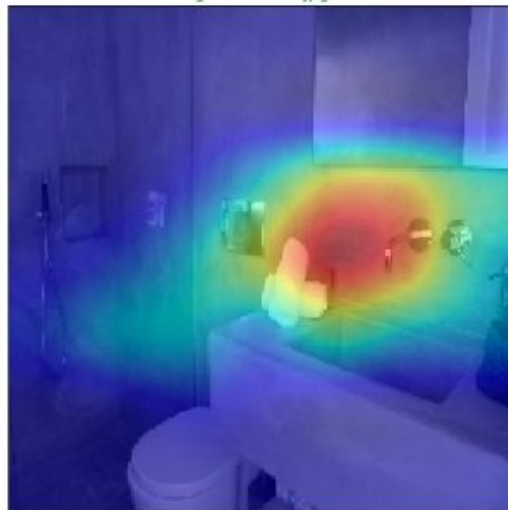
Bathroom correct classification

g172736587.jpg



True: Bathroom | Pred: Bathroom

g242557547.jpg



True: Bathroom | Pred: Bathroom

g124314371.jpg



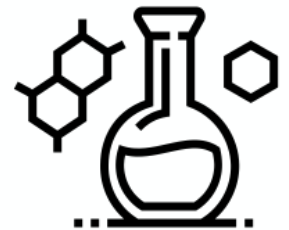
True: Bathroom | Pred: Bathroom



Using faucets to correctly identify Bathroom.

Learnings so far

- Attribution techniques like CAM lend interpretability
- CAM can drive data collection in specific directions



Tagging Next Steps

1. Add still more data
 - a. Explore manual tagging options for training
(Example: Amazon Mechanical Turk)
2. Add more classes
 - a. Fitness Studio
 - b. Conference Room
 - c. Other

Image Aesthetics

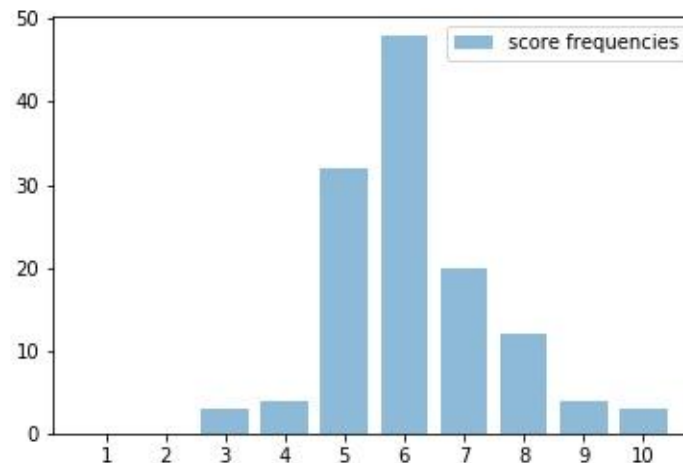
Ground Truth Labels

For the NIMA model we need “true” probability distribution over all classes for each image:

- AVA dataset: we have frequencies over all classes for each image
→ normalize frequencies to get “true” probability distribution



(6.151 / 1.334)



We have gone through two iterations of the aesthetic model:

- First iteration - Train on AVA Dataset
- Second iteration - Fine-tune first iteration model on in-house labelled data



Results - first iteration

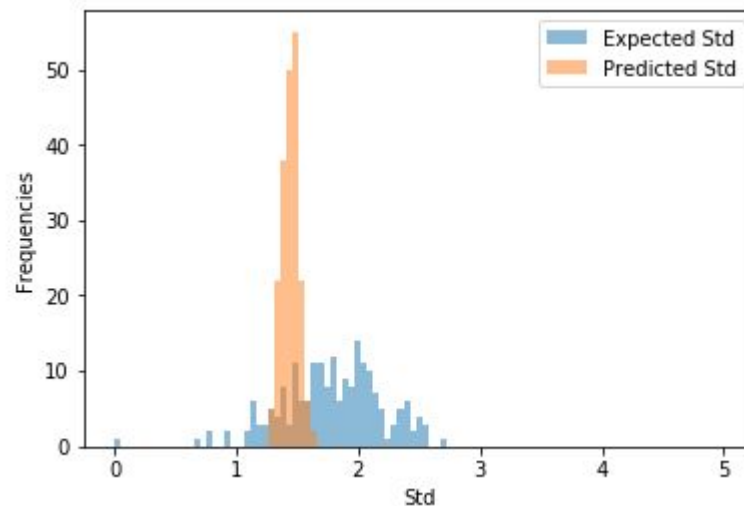
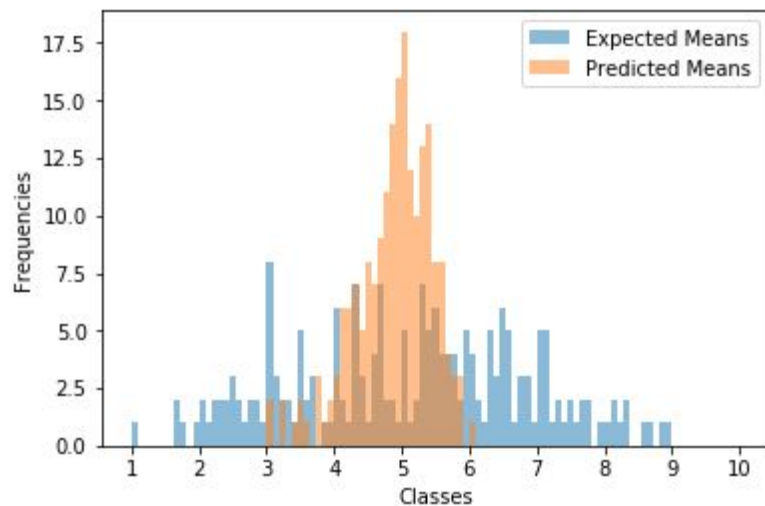
Aesthetic model - MobileNet

Linear correlation coefficient (LCC): 0.5987

Spearman's correlation coefficient (SCRR): 0.6072

Earth Mover's Distance: 0.2018

Accuracy (threshold at 5): 0.74



Examples - first iteration

Aesthetic model

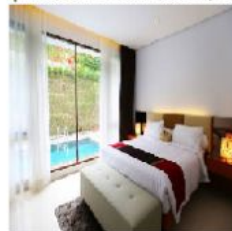
predicted: 4.909; rank 1/12



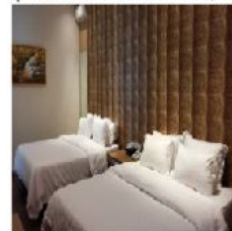
predicted: 4.854; rank 2/12



predicted: 4.818; rank 3/12



predicted: 4.694; rank 4/12



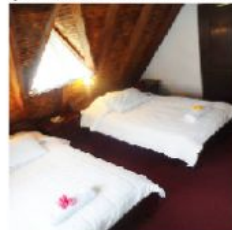
predicted: 4.522; rank 5/12



predicted: 4.46; rank 6/12



predicted: 4.247; rank 7/12



predicted: 4.169; rank 8/12



predicted: 4.166; rank 9/12



predicted: 4.162; rank 10/12



predicted: 4.064; rank 11/12



predicted: 4.048; rank 12/12



Examples - first iteration

Aesthetic model

predicted: 5.056; rank 1/12



predicted: 4.952; rank 2/12



predicted: 4.82; rank 3/12



predicted: 4.814; rank 4/12



predicted: 4.704; rank 5/12



predicted: 4.678; rank 6/12



predicted: 4.663; rank 7/12



predicted: 4.606; rank 8/12



predicted: 4.564; rank 9/12



predicted: 4.338; rank 10/12



predicted: 4.126; rank 11/12



predicted: 3.997; rank 12/12



Examples - first iteration

Aesthetic model



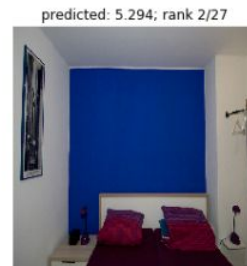
2 Personen 16 m² 1 Schlaf-Zi
Cosy Room in Quiet Location

pro Nacht, Ø
ab **47 €**

⊙ 8,0 km Stadtzentrum [Karte](#)
Kochgelegenheit | TV

Infos [Verfügbarkeit prüfen](#)

zum Angebot
bei Wimdu >



Examples - first iteration

Aesthetic model



Aquarium Suite Genova
© 1,1 km Stadtzentrum Karte

90 Exzellent
1 Bewertung

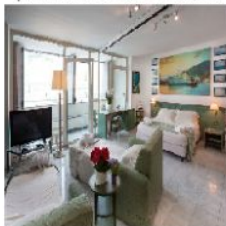
WLAN, Klimaanlage, Bad, Nichtraucherzimmer, Parkplatz, T...

Booking.com pro Nacht **164 €**
328 € / 2N

Apartment - nicht kostenfrei stornie...

164 € / Nacht
Zum Anbieter

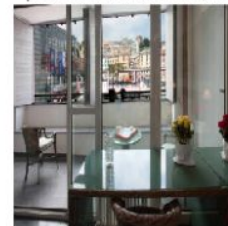
predicted: 5.266; rank 1/13



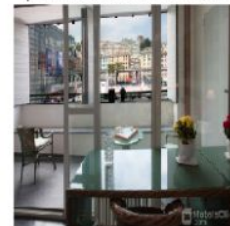
predicted: 5.021; rank 2/13



predicted: 5.014; rank 3/13



predicted: 4.921; rank 4/13



predicted: 4.892; rank 5/13



predicted: 4.838; rank 6/13



predicted: 4.832; rank 7/13



predicted: 4.819; rank 8/13



predicted: 4.811; rank 9/13



predicted: 4.775; rank 10/13



predicted: 4.757; rank 11/13



predicted: 4.55; rank 12/13



Examples - first iteration

Aesthetic model



Best Season Apart Hotel
★★★ @ 0,9 km Stadtzentrum [Karte](#)
WLAN, Sauna, Shuttle Service, Kochgelegenheit

Booking.com pro Nacht **42 €**
Apartment - Michailowska Straße 2... 84 € / 2N
Stornierung kostenlos

84 Super
843 Bewertungen

42 € / Nacht
[Zum Anbieter >](#)

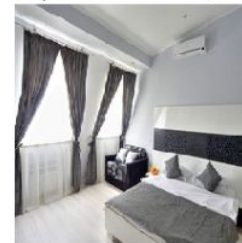
predicted: 5.115; rank 1/50



predicted: 5.103; rank 2/50



predicted: 5.095; rank 3/50



predicted: 5.062; rank 4/50



predicted: 5.043; rank 5/50



predicted: 4.95; rank 6/50



predicted: 4.943; rank 7/50



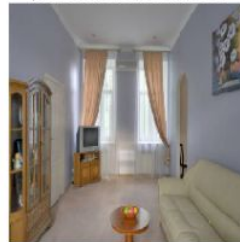
predicted: 4.888; rank 8/50



predicted: 4.888; rank 9/50



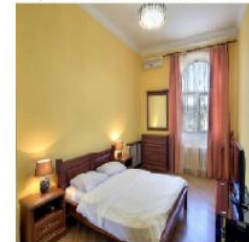
predicted: 4.842; rank 10/50



predicted: 4.835; rank 11/50



predicted: 4.831; rank 12/50



Results - second iteration

- We built a simple labeling application
- <http://image-aesthetic-labelling-app-nima.apps.eu.idealo.com/>
- ~ 12 people from idealo Reise and Data Science labeled
 - 1000 hotel images for aesthetics
- We fine-tuned the aesthetic model with 800 training images
- Built aesthetic test dataset with 200 images

Results - second iteration

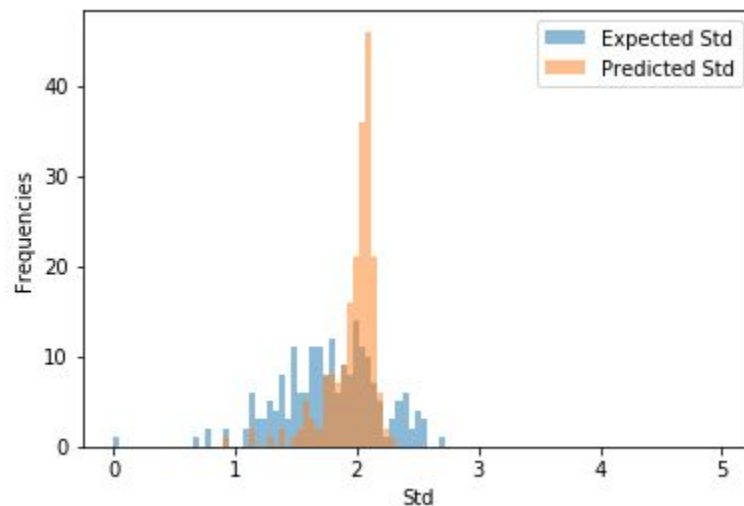
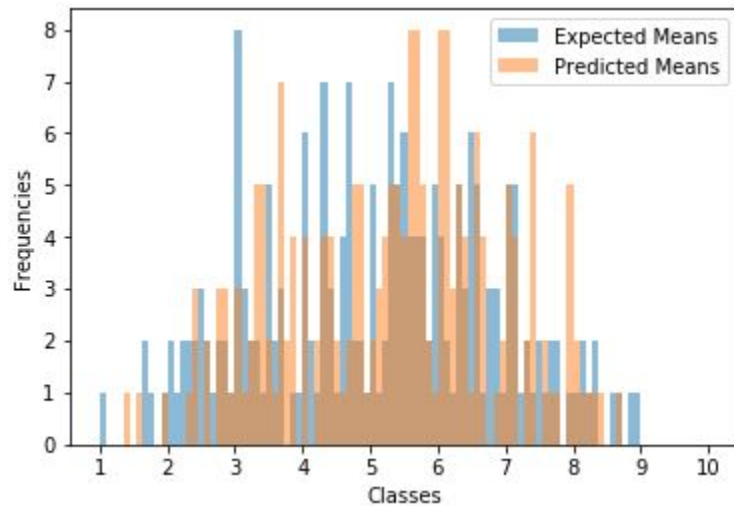
Aesthetic model - MobileNet

Linear correlation coefficient (LCC): 0.7986

Spearman's correlation coefficient (SCRR): 0.7743

Earth Mover's Distance: 0.1236

Accuracy (threshold at 5): 0.85



Examples - second iteration

Aesthetic model

predicted: 6.094; rank 1/12



predicted: 5.796; rank 2/12



predicted: 5.699; rank 3/12



predicted: 5.61; rank 4/12



predicted: 5.456; rank 5/12



predicted: 4.253; rank 6/12



predicted: 4.18; rank 7/12



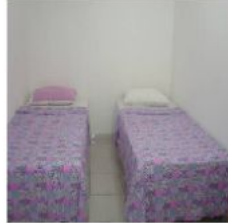
predicted: 4.175; rank 8/12



predicted: 3.459; rank 9/12



predicted: 3.225; rank 10/12



predicted: 3.141; rank 11/12



predicted: 3.048; rank 12/12



Examples - second iteration

Aesthetic model

predicted: 5.359; rank 1/12



predicted: 5.142; rank 2/12



predicted: 4.482; rank 3/12



predicted: 4.422; rank 4/12



predicted: 4.16; rank 5/12



predicted: 4.113; rank 6/12



predicted: 3.889; rank 7/12



predicted: 3.769; rank 8/12



predicted: 3.693; rank 9/12



predicted: 3.629; rank 10/12



predicted: 2.979; rank 11/12

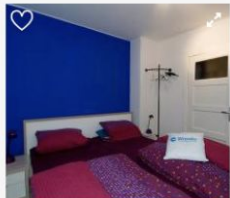


predicted: 2.458; rank 12/12



Examples - second iteration

Aesthetic model



2 Personen 16 m² 1 Schlaf-Zi
Cosy Room in Quiet Location

8,0 km Stadtzentrum [Karte](#)
Kochgelegenheit | TV
Infos [▼](#)

pro Nacht, Ø
ab **47 €**

zum Angebot >
bei Wimdu

[Verfügbarkeit prüfen](#)

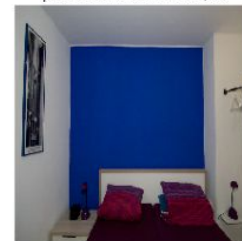
predicted: 6.39; rank 1/27



predicted: 5.431; rank 2/27



predicted: 5.232; rank 3/27



predicted: 5.159; rank 4/27



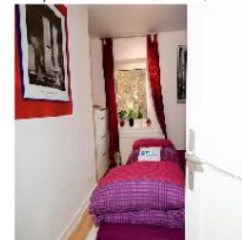
predicted: 5.1; rank 5/27



predicted: 5.07; rank 6/27



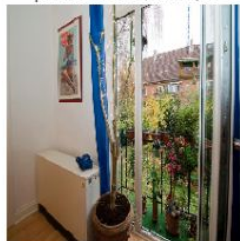
predicted: 5.025; rank 7/27



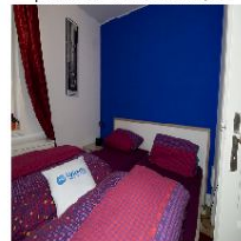
predicted: 4.893; rank 8/27



predicted: 4.855; rank 9/27



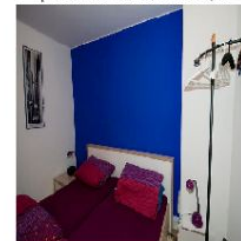
predicted: 4.773; rank 10/27



predicted: 4.769; rank 11/27



predicted: 4.741; rank 12/27



Examples - second iteration

Aesthetic model

Aquarium Suite Genova
 1,1 km Stadtzentrum [Karte](#)
 WLAN, Klimaanlage, Bad, Nichtraucherzimmer, Parkplatz, T...

Booking.com pro Nacht **164 €**
 Apartment - nicht kostenfrei stornie... 328 € / 2N

90 Exzellent
 1 Bewertung

164 € / Nacht
 Zum Anbieter >

predicted: 7.613; rank 1/13



predicted: 6.538; rank 2/13



predicted: 6.459; rank 3/13



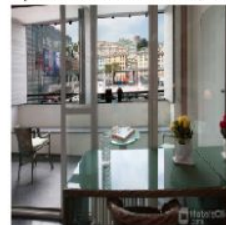
predicted: 6.248; rank 4/13



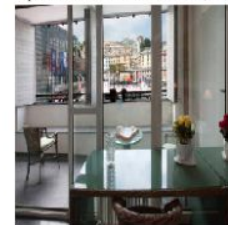
predicted: 6.227; rank 5/13



predicted: 6.043; rank 6/13



predicted: 5.884; rank 7/13



predicted: 5.421; rank 8/13



predicted: 4.995; rank 9/13



predicted: 4.588; rank 10/13



predicted: 4.553; rank 11/13

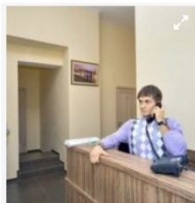


predicted: 4.382; rank 12/13



Examples - second iteration

Aesthetic model



Best Season Apart Hotel

★★★ 0,9 km Stadtzentrum [Karte](#)

WLAN, Sauna, Shuttle Service, Kochgelegenheit

B Booking.com

Apartment - Michailowska Straße 2...

Stornierung kostenlos

pro Nacht **42 €**

84 € / 2N

84 Super
843 Bewertungen

42 € / Nacht
Zum Anbieter →

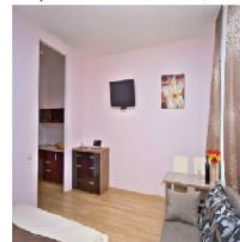
predicted: 7.281; rank 1/50



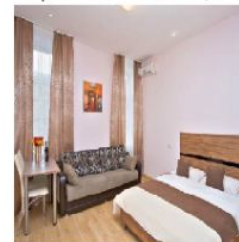
predicted: 6.734; rank 2/50



predicted: 6.546; rank 3/50



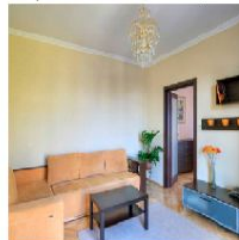
predicted: 6.447; rank 4/50



predicted: 6.053; rank 5/50



predicted: 5.851; rank 6/50



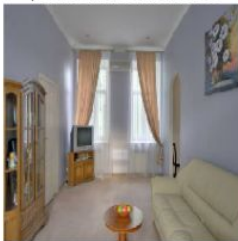
predicted: 5.845; rank 7/50



predicted: 5.815; rank 8/50



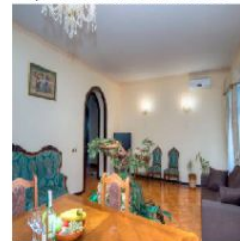
predicted: 5.634; rank 9/50



predicted: 5.616; rank 10/50



predicted: 5.535; rank 11/50



predicted: 5.519; rank 12/50



Production Aesthetic model

OPENSIFT ORIGIN

reise-hotel-image

Overview

Applications

BUILDS

Resources

Storage

Monitoring

APPLICATION

accommodation-image-service <http://accommodation-image-service-reise-hotel-image.apps.eu.idealoo.com>

DEPLOYMENT

accommodation-image-service, #53

2.7 Gib Memory 0.01 Cores CPU 16 Kib/s Network 20 pods

APPLICATION

hotel-image-assessment-aesthetic-server <http://hotel-image-assessment-aesthetic-server-reise-hotel-image.apps.eu.idealoo.com>

DEPLOYMENT

hotel-image-assessment-aesthetic-server, #26

CONTAINER: HOTEL-IMAGE-ASSESSMENT-AESTHETIC-SERVER

- Image: reise-hotel-image/hotel-image-assessment-aesthetic-server 93c9c1c 397.3 MiB
- Build: hotel-image-assessment-aesthetic-server, #9
- Source: DS-109: Enable to load truncated images. e96595b
- Ports: 8080/TCP

Networking

SERVICE Internal Traffic

hotel-image-assessment-aesthetic-server

8080/TCP (8080-tcp) → 8080

BUILDS

hotel-image-assessment-aesthetic-server

✓ Build #9 is complete created 3 days ago

1.5 Gib Memory

2.0 Cores CPU

86 Kib/s Network

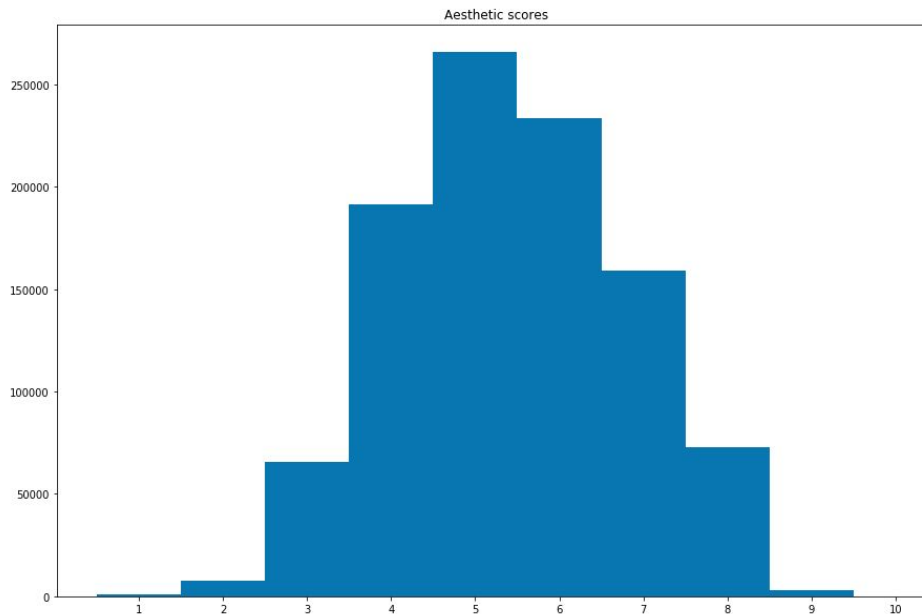
Average Usage Last 15 Minutes

100 pods

Production

Aesthetic model

- To date we have scored ~280 million images
- Distribution of scores (sample of 1 million scores):



Production - Low Scores

Aesthetic model

score: 2.604



score: 2.914



score: 2.944



score: 2.998



score: 2.976



score: 2.764



score: 2.422



score: 2.422



score: 2.764



score: 2.42



score: 2.977



score: 2.932



score: 2.765



score: 2.932



score: 2.551



score: 2.864



score: 2.383



score: 2.383



score: 2.716



score: 2.716



Production - Medium Scores

Aesthetic model

score: 4.549



score: 4.218



score: 4.909



score: 4.218



score: 4.596



score: 4.655



score: 4.666



score: 4.614



score: 4.884



score: 4.472



score: 4.859



score: 4.295



score: 4.106



score: 4.692



score: 4.334



score: 4.928



score: 4.596



score: 4.966



score: 4.441



score: 4.62



Production - High Scores

Aesthetic model

score: 7.018



score: 7.018



score: 7.797



score: 7.021



score: 7.276



score: 7.47



score: 7.298



score: 7.592



score: 7.29



score: 7.236



score: 7.391



score: 7.021



score: 7.062



score: 7.018



score: 7.843



score: 7.592



score: 8.025



score: 7.169



score: 7.854



score: 7.619

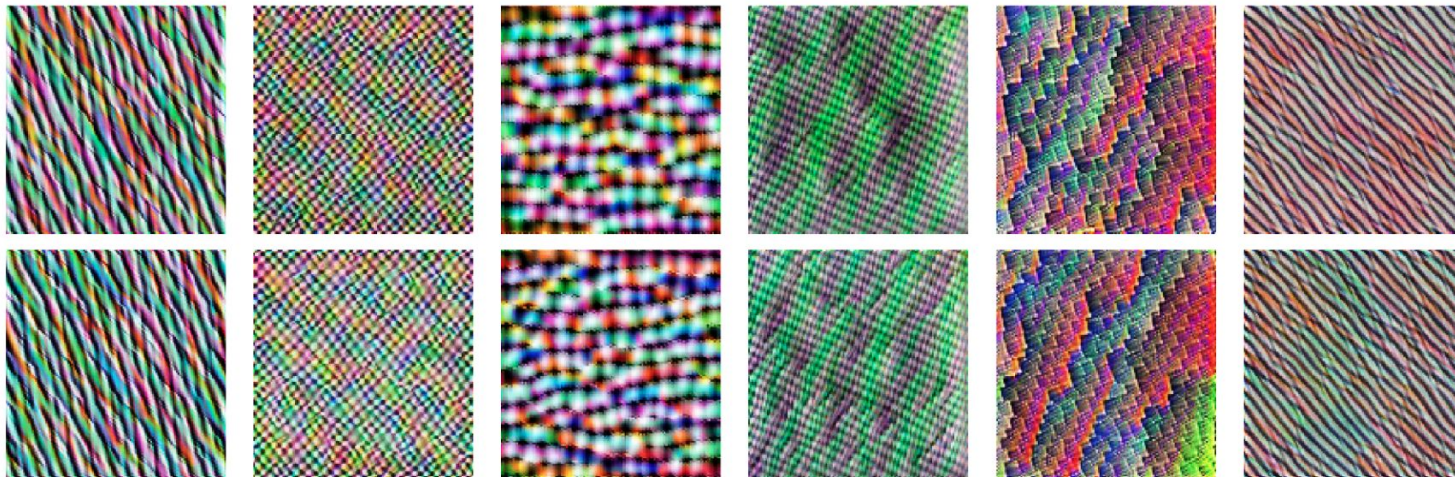


Understanding Model Decisions



Convolutional Filter Visualisations

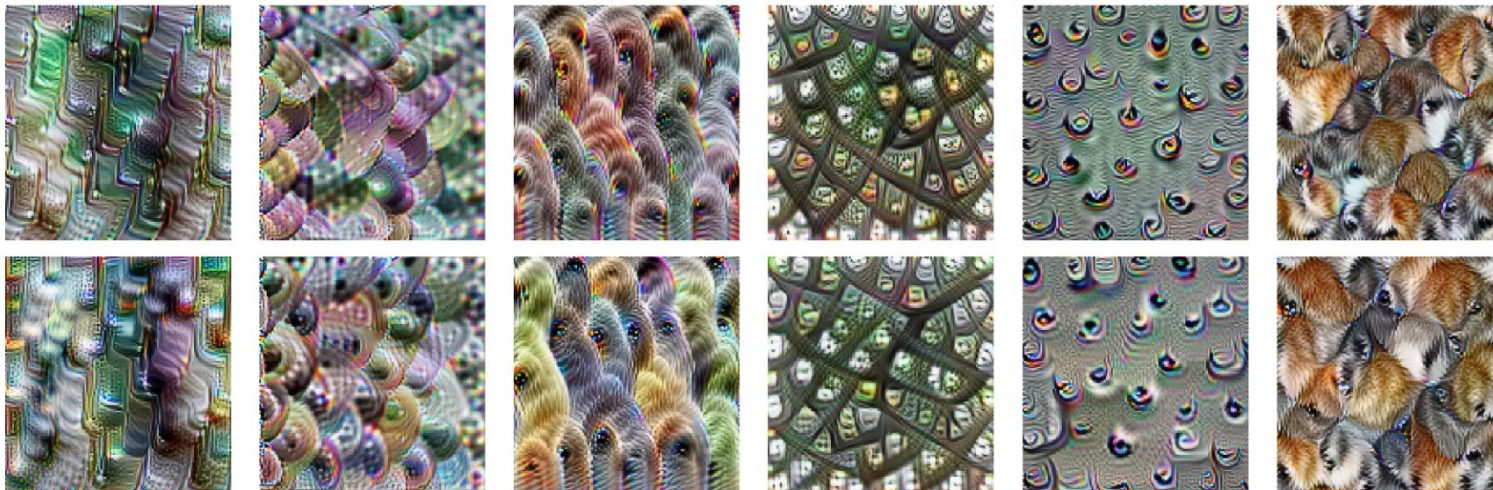
Layer 23 MobileNet original



MobileNet Aesthetic

Convolutional Filter Visualisations

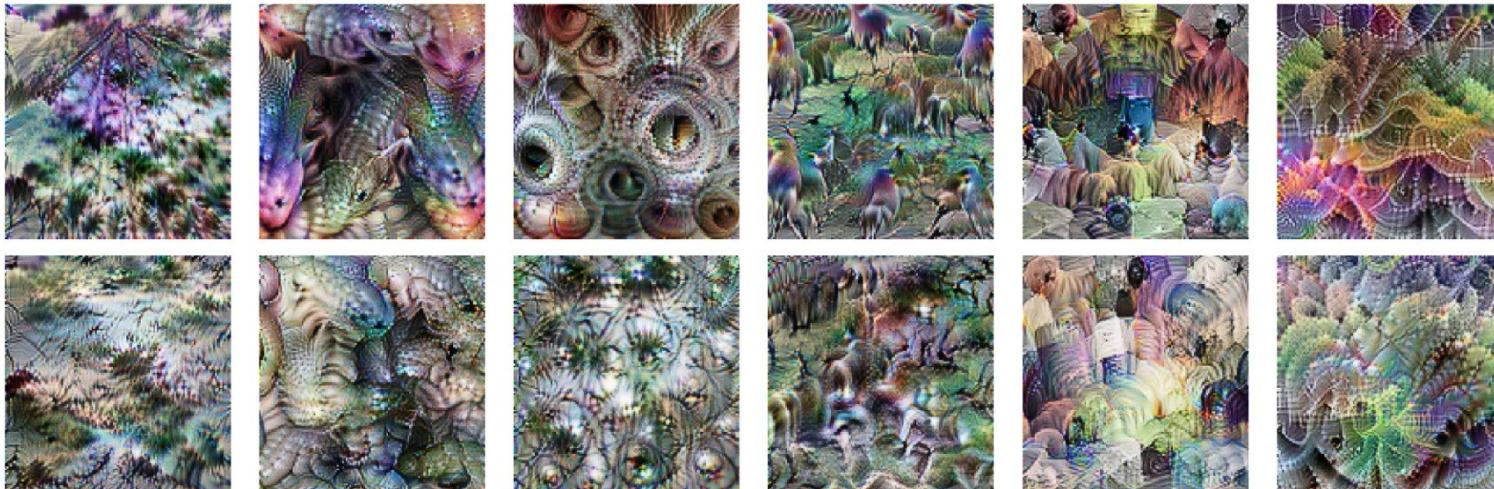
Layer 51 MobileNet original



MobileNet Aesthetic

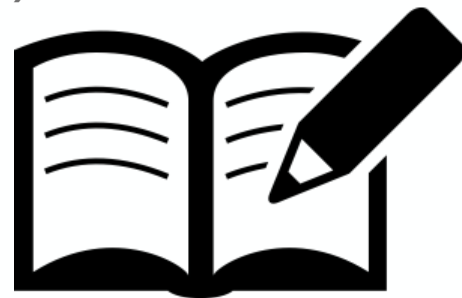
Convolutional Filter Visualisations

Layer 79 MobileNet original



MobileNet Aesthetic

- **Hotel specific labeled data is key** - Aesthetic model improved markedly from 800 additional training samples
- NIMA only requires **few samples** to achieve **good results** (EMD loss)
- Labeled hotel images also important for **test set** (model evaluation)
- Training on GPU significantly improved training time (**~30 fold**)



Aesthetics Next Steps

- Continue labeling images for aesthetic classifier
- Introduce new desirable biases in labeling (e.g. low technical quality == low aesthetics)
- Improve prediction speed of models (e.g. lighter CNN architectures)



Summary

Summary

- Transfer learning allowed us to train image tagging and aesthetic classifiers with a few thousand domain specific samples
- Showed the importance of having noise-free data for quality predictions
- Use of attribution & visualization techniques helps understand model decisions and improve them



Check us out! #idealoTech

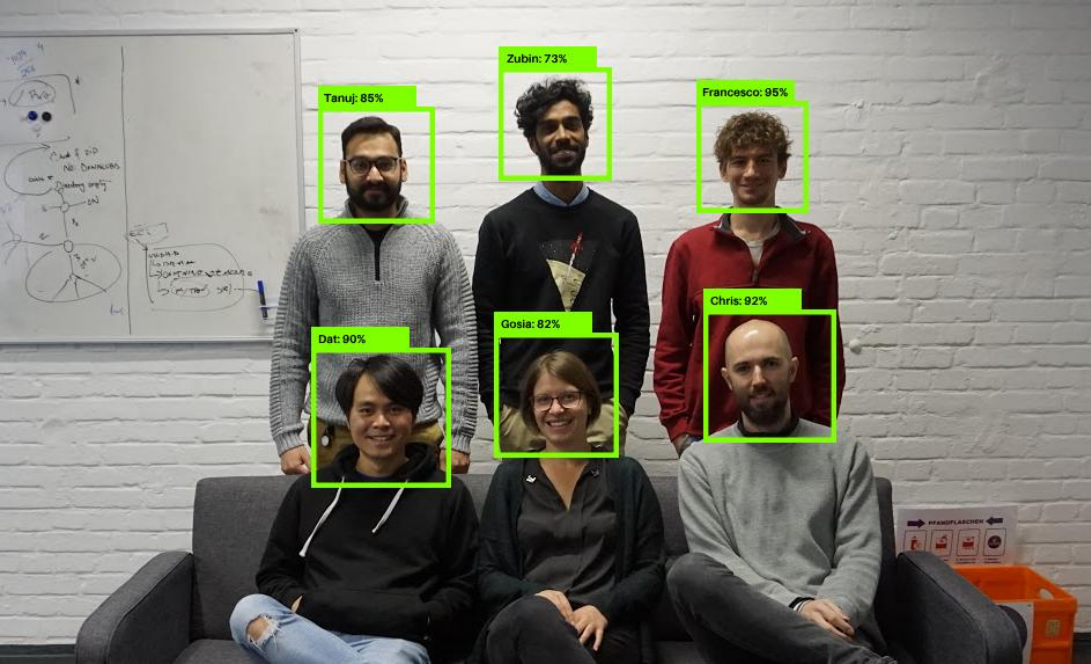


<https://github.com/idealo>



<https://medium.com/idealo-tech-blog>

We're hiring!



Data Engineers, DevOps Engineers across different teams
Check out our job postings: jobs.ideal.de

Tanuj Jain

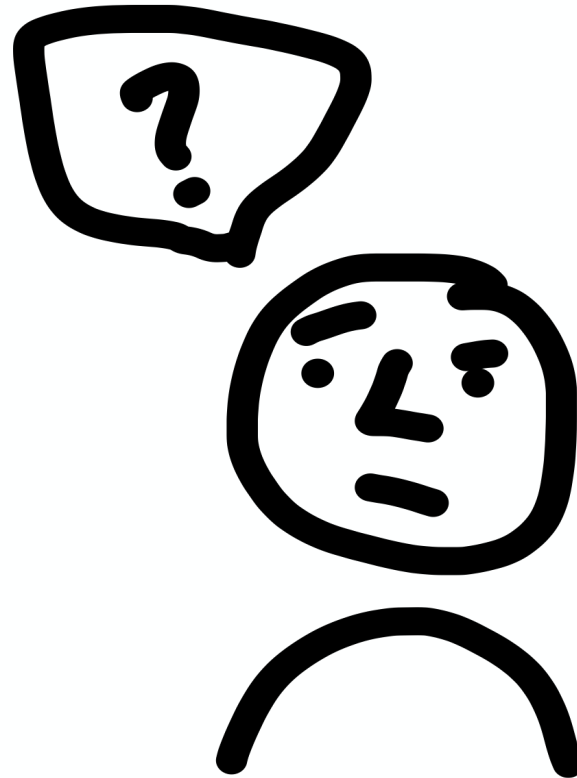
tanuj.jain@idealo.de

@tjainn

Christopher Lennan

christopher.lennan@idealo.de

@chris_lennan



THE END