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Image Data for Machine Learning Research in Marketing

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Why Use Image Data with Machine Learning for Marketing Research?



- 1 More than 6.5 billion images shared every day¹
- 2 More than 60% of US adults use instagram²



Automatically extract information for analysis

Predict behavior



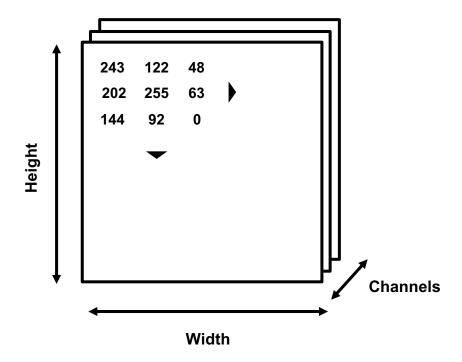
Goal always generalization on unseen data



Hartmann, J., Heitmann, M., Schamp, C., & Netzer, O. (2021). The power of brand selfies. Journal of Marketing Research, 58(6), 1159-1177.

³¹ Mind-Boggling Instagram Stats & Facts for 2022, https://www.wordstream.com/blog/ws/2017/04/20/instagram-statistics

The 4 dimensions of image data





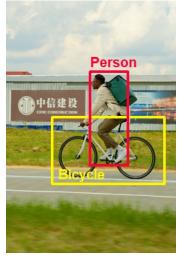
The 4 dimensions of image data from PIL import Image import numpy as np Image = Image.open('path/to/image.jpg') Array = np.array(Image) 166 255





A multitude of potential tasks for image data







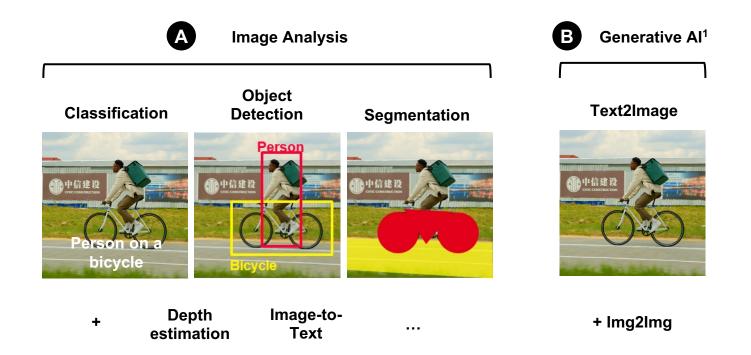
Classification

Object Detection

Segmentation



A multitude of potential tasks for image data



Tools to annotate your data

Generative Al





Segmentation, depth detection



Python labeling notebook

https://github.com/Maximilianwte/Image-tutorial/blob/main/Image_labeling.ipynb

Task

Format

Tools



Classification,

Folders, Tables

- 1. Move images to folder
- 2. PhotoSift¹
- 3. Use Python GUI

JSON, XML

- 1. Labelme²
- 2. V7³
- 3. Labelbox⁴

Image, JSON

- 1. Labelme²
- 2. V7³
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Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

¹ PhotoSift (freeware) available for windows: https://www.rlvision.com/photosift/about.php

² Labelme (freeware) available for windows, mac and linux: https://github.com/wkentaro/labelme

³ V7 (free for education) available online: https://www.v7labs.com

⁴ Labelbox (freemium) available online: https://labelbox.com/



Using Images for analysis

Table 3. Summary Statistics of Field Data.

Variable	Twitter		Instagram		Display Ads	
	Mean	SD	Mean	SD	Mean	SD
Dependent Variables						
Likes	5.06	233.79	255.33	4,380.30	_	_
Comments	.43	7.00	9.85	65.53	_	_
Purchase Intentions	.02	.15	.51	2.72	_	_
Brand-Image Type						
Brand Selfie ^a	28.73	_	19.63	_	72.68	_
Consumer Selfie ^a	7.93	_	11.57	_	18.80	_
Packshot ^a	63.35	_	68.80	_	8.51	_
Image Characteristics						
Logo Size	.12	.14	.07	.10	.33	.21
Logo Centrality	.63	.23	.63	.19	.81	.14
Visual Complexity	-1.96	.43	-2.09	.55	-1.40	.94
Brightness	.51	.15	.56	.13	.60	.13
Brightness Contrast	.25	.05	.26	.05	.24	.05
Post Characteristics						
Number of Words	2.20	.55	3.24	.82	2.29	.22
Number of Hashtags	.39	.59	2.29	.92	_	_
Number of Handletags	.23	.39	.25	.47	_	_
Branded Caption ^a	6.23	_	12.10	_	_	_
Branded Tag ^a	13.02	_	61.65	_	_	_
Ad Tag ^a	.35	_	2.35	_	_	_
First-Person Pronouna	35.66	_	28.97	_	.13	_
Second-Person Pronouna	14.59	_	16.79	_	35.25	_
Question Word Share	.01	.04	.01	.03	.01	.03
Netspeak Word Share	.02	.06	.01	.03	.00	.0
Positive Sentiment ^a	42.43	_	50.84	_	6.12	_
Neutral Sentiment ^a	46.25	_	45.24	_	92.73	_
Negative Sentiment ^a	11.32	_	3.92	_	1.15	_
Post Age	5.04	.64	2.39	1.48	_	_

Choosing a library for deep learning



Developed by Google

Keras High-level API

Support for GPU's and TPU's



Developed by Meta

Pythonic syntax

Steep learning curve



HUGGING FACE

Large amount of pre-trained models

Easy-to-use

Support for PyTorch and TensorFlow



Preparing the data

The goal of ML is generalization → Simulate situation of having unseen data

- 1 Load data
- 2 Data Splitting
- Train-test-split: Split off percentage of training data for testing
- K-fold cross-validation: Split data in k equal datasets. Iterate over all subsets using each as validation dataset
- Bootstrapping: Create artificial datasets by randomly sampling observations
 - 3 Feature extraction





```
from datasets import load_dataset

dataset = load_dataset("imagefolder",
data_dir="path/to/directory")
```



```
from sklearn.model_selection import
train_test_split

train_dataset, test_dataset =
train_test_split(dataset, test_size=0.2,
random_state=42)
```

```
from transformers import ViTFeatureExtractor
feature_extractor = ViTFeatureExtractor.
  from_pretrained('google/vit-base')

def prepare(example_batch):
  inputs = feature_extractor([x for x in
    example_batch['image']],
  return_tensors='pt')
  inputs['labels'] = example_batch['label']
  return inputs

prepared_ds = dataset.with_transform(prepare)
```

Increasing data variability by using Image Augmentations

Use augmentations to efficiently increase variability of the training data



More variability in data leads to better generalization



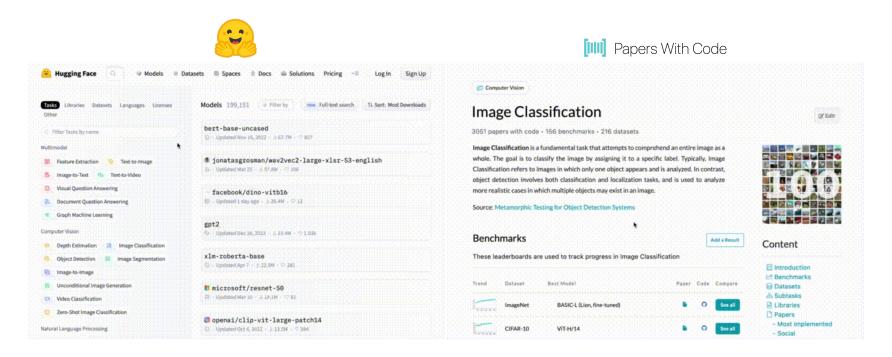
```
from torchvision import transforms

transform = transforms.Compose([
  transforms.ColorJitter(hue=0.5),
  transforms.RandomRotation(30),
  transforms.RandomHorizontalFlip(),
  transforms.Resize((512, 512))
])

img_transformed = transform(img)
```



Resources to find a good model





Training the model

- Process of training the model
- Question of optimal hyperparameters for training



- Grid search, Random search, Bayesian Optimization
- Automated libraries for tuning hyperparameters

Training (without automated Hyperparameter tuning)



```
from transformers import
ViTForImageClassification
model =
  ViTForImageClassification.from pretrai
   ned("google/vit-base").to('cuda')
training args = TrainingArguments(
per device train batch size=64,
evaluation strategy="steps",
num_train_epochs=20,
logging steps=50,
learning rate=1e-4,
trainer = Trainer(
    model=model.
    args=training args)
train results = trainer.train()
```

Training (with automated Hyperparameter tuning)

study.best params

```
import optuna
   from transformers import
   ViTForImageClassification
model =
                               tutorial/blob/main/lmage_Classification in
   ViTForImageClassification.
   ned("google/vit-base").to('cuda')
def objective(trial):
   training_args = TrainingArguments(
   per device train batch size=trial.suggest c
      ategorical('batch size', [16,32,64]),
   evaluation strategy="steps",
   num train epochs=20,
  logging steps=50,
   learning rate=trial.suggest float('lr', 1e-
      5, 1e-3),
   load best model at end=True,
   trainer = Trainer(
      model=model.
      args=training args)
   train results = trainer.train()
   return train results['eval accuracy']
studv =
   optuna.create study(direction='maximize')
study.optimize(objective, n trials=100)
```



Python image

classification

Finally using your model to predict on new data

Model









Inside

Outside

3.75

4.52





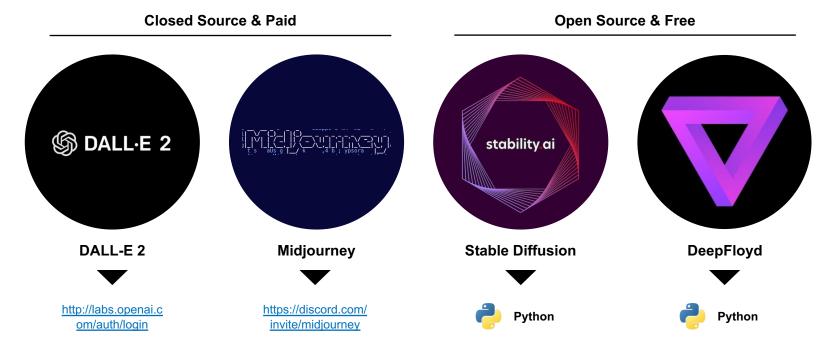
B

Using Generative Al





Diffusion models revolutionizing generative computer vision since 2022





Generating images can be done from text prompts or with an input image to transform

Prompting



lmg2lmg



Inpainting



Outpainting





Generating Images using Stable Diffusion









Getting your data into the model



Adapting an Input Image



Fine-tuning the weights and embeddings of the model



pipe(prompt="Photo of xyzperson holding a handcreme", height=512, width=512, guidance_scale=7.5).images[0]



Currently only with Stable Diffusion and DeepFloyd



Possible with all models



Fine-tuning SD Dreambooth

tutorial/blob/main/Finetuning Stable-Diffusion Dreambooth.ipvnb

A few principles on working with machine learning models

- 1 Generalization is key
- 2 Leverage pre-trained

3 Better data trumps a larger model

- 4 Get fitting architecture and loss function
- 5 Prefer the simpler model



Resources

Presentation GitHub Repository



https://github.com/Maximilianwte/Image-tutorial

Blogs

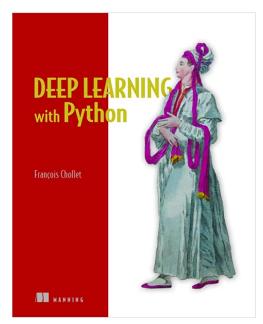


https://huggingface.co/docs



https://towardsdatascience.com/

Book Recommendation



https://www.manning.com/books/deep-learning-with-python



Contact



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University of Hamburg

#Unstructured data #Generative AI #Decision Aids



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