Welcome to Colab!

Explore the Gemini API

The Gemini API gives you access to Gemini models created by Google DeepMind. Gemini models are built from the ground up to be multimodal, so you can reason seamlessly across text, images, code, and audio.

How to get started

1. Go to Google AI Studio and log in with your Google account.
2. Create an API key.
3. Use a quickstart for Python, or call the REST API using curl.

Explore use cases

- Create a marketing campaign
- Analyze audio recordings
- Use System instructions in chat

To learn more, check out the Gemini cookbook or visit the Gemini API documentation.

```
Start coding or generate with AI.
```

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/content/archive (3).zip'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import copy
import torch
import numpy as np
import pandas as pd
import torch.nn as nn
import torchvision
from torchvision import models
from sklearn.utils import shuffle
from torchvision import datasets, transforms
from torch.utils.data import Dataset, DataLoader
from PIL import Image
from tqdm import tqdm
import matplotlib.pyplot as plt
import matplotlib.font_manager
from collections import OrderedDict
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from keras.preprocessing.image import ImageDataGenerator
```

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

```
device(type='cpu')
```

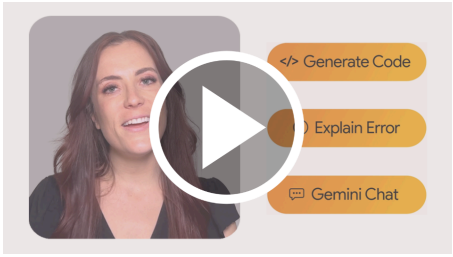
```
import os
print(os.getcwd())
```

```
/content
```

```
if "food-101" in os.listdir():
    print("Dataset already exists")
else:
    print("Downloading the data...")
    !wget http://data.vision.ee.ethz.ch/cvl/food-101.tar.gz
    print("Dataset downloaded!")
    print("Extracting data..")
    !tar xzvf food-101.tar.gz > /dev/null 2>&1
    print("Extraction done!")
```

```
Downloading the data...
--2024-07-08 16:16:42--  http://data.vision.ee.ethz.ch/cvl/food-101.tar.gz
Resolving data.vision.ee.ethz.ch (data.vision.ee.ethz.ch)... 129.132.52.178, 2001:67c:10ec:36c2::178
Connecting to data.vision.ee.ethz.ch (data.vision.ee.ethz.ch)|129.132.52.178|:80... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://data.vision.ee.ethz.ch/cvl/food-101.tar.gz [following]
--2024-07-08 16:16:42--  https://data.vision.ee.ethz.ch/cvl/food-101.tar.gz
Connecting to data.vision.ee.ethz.ch (data.vision.ee.ethz.ch)|129.132.52.178|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 4996278331 (4.7G) [application/x-gzip]
Saving to: ‘food-101.tar.gz’

food-101.tar.gz     100%[===================>]   4.65G  23.6MB/s    in 3m 36s

2024-07-08 16:20:19 (22.1 MB/s) - ‘food-101.tar.gz’ saved [4996278331/4996278331]

Dataset downloaded!
Extracting data..
Extraction done!
```

Colab now has AI features powered by Gemini. The video below provides information on how to use these features, whether you're new to Python, or a seasoned veteran.




```
# Target the file containing the list of classes within the directory
classes_file_path = "/content/food-101/meta/classes.txt"
classes = open(classes_file_path, 'r').read().splitlines()
classes_21 = classes[:20] + ['other']
classes_21, len(classes_21)
```

```
(['apple_pie',
  'baby_back_ribs',
  'baklava',
  'beef_carpaccio',
  'beef_tartare',
  'beet_salad',
  'beignets',
  'bibimbap',
  'bread_pudding',
  'breakfast_burrito',
  'bruschetta',
  'caesar_salad',
  'cannoli',
  'caprese_salad',
  'carrot_cake',
  'ceviche',
  'cheesecake',
  'cheese_plate',
  'chicken_curry',
  'chicken_quesadilla',
  'other'],
 21)
```

```
!echo "Testing images"
!head -n 5 ./food-101/meta/test.txt
!echo -e "\nTraining images"
!head -n 5 ./food-101/meta/train.txt | head -n 5
```

```
Testing images
apple_pie/1011328
apple_pie/101251
apple_pie/1034399
apple_pie/103801
apple_pie/1038694
```

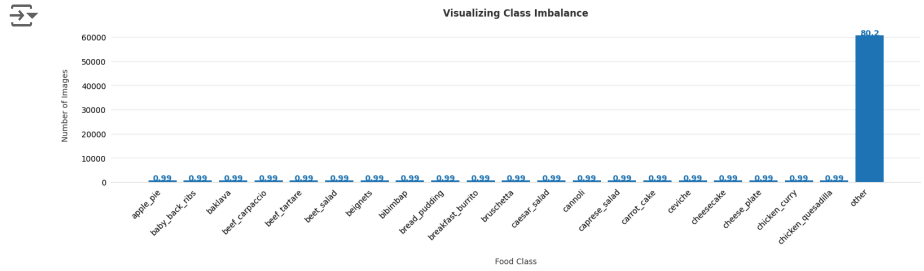
```
 Training images
 apple_pie/1005649
 apple_pie/1014775
 apple_pie/1026328
 apple_pie/1028787
 apple_pie/1043283
```

```
def prep_df(path: str) -> pd.DataFrame:
    array = open(path, 'r').read().splitlines()

    # Getting the full path for the images
    img_path = "./food-101/images/"
    full_path = [img_path + img + ".jpg" for img in array]
    # Splitting the image index from the label
    imgs = []
    for img in array:
        img = img.split('/')

        imgs.append(img)

    imgs = np.array(imgs)
    # Converting the array to a data frame
    imgs = pd.DataFrame(imgs[:,0], imgs[:,1], columns=['label'])
    # Adding the full path to the data frame
    imgs['path'] = full_path

    # Randomly shuffling the order to the data in the dataframe
    imgs = shuffle(imgs)

    return imgs


train_imgs = prep_df('./food-101/meta/train.txt')
test_imgs = prep_df('./food-101/meta/test.txt')

train_imgs.head(5)
```

	label	path
3157604	escargots	./food-101/images/escargots/3157604.jpg
1724365	lobster_roll_sandwich	./food-101/images/lobster_roll_sandwich/172436...
3449517	takoyaki	./food-101/images/takoyaki/3449517.jpg
3090440	peking_duck	./food-101/images/peking_duck/3090440.jpg
3154879	lobster_bisque	./food-101/images/lobster_bisque/3154879.jpg

```
plt.figure(figsize=(20, 5))

num_rows = 3
num_cols = 8


for idx in range(num_rows * num_cols):
    random_idx = np.random.randint(0, train_imgs.shape[0])
    img = plt.imread(train_imgs.path.iloc[random_idx])

    label = train_imgs.label.iloc[random_idx]

    ax = plt.subplot(num_rows, num_cols, idx + 1)
    plt.imshow(img)
    plt.title(label)
    plt.axis("off")
```


```
def barplot_vis(imgs_dataframe):# Use the newly integrated Roboto font family for all text.
    fig, ax = plt.subplots()

    new_labels = [row if row in classes_21 else "other" for row in imgs_dataframe.label]
    tmp_imgs_dataframe = imgs_dataframe.copy(deep=True)
    tmp_imgs_dataframe['label'] = new_labels

    grouped_train_imgs = tmp_imgs_dataframe.groupby("label")

    heights = [grouped_train_imgs.get_group(group).shape[0] for group in classes_21]

    # Save the chart so we can loop through the bars below.
    bars = ax.bar(
        x=classes_21,
        height=heights,
        tick_label=classes_21
    )

    # Axis formatting.
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.spines['left'].set_visible(False)
    ax.spines['bottom'].set_color('#DDDDDD')
    ax.tick_params(bottom=False, left=False)
    ax.set_axisbelow(True)
    ax.yaxis.grid(True, color='#EEEEEE')
    ax.xaxis.grid(False)

    # Add text annotations to the top of the bars.
    bar_color = bars[0].get_facecolor()
    percentage_heights = np.array(heights) / sum(heights)
    for idx in range(len(bars)):
      ax.text(
          bars[idx].get_x() + bars[idx].get_width() / 2,
          bars[idx].get_height() + 0.3,
          round(percentage_heights[idx] * 100, 2),
          horizontalalignment='center',
          color=bar_color,
          weight='bold'
      )

    # Add labels and a title.
    ax.set_xlabel('Food Class', labelpad=15, color='#333333')
    ax.set_ylabel('Number of Images', labelpad=15, color='#333333')
    ax.set_title('Visualizing Class Imbalance', pad=15, color='#333333',
                 weight='bold')

    fig.autofmt_xdate(rotation=45)
    fig.set_size_inches(18.5, 4)


barplot_vis(train_imgs)
```




```
train_transforms = transforms.Compose([transforms.RandomRotation(30),
                                       transforms.RandomResizedCrop(224),
                                       transforms.RandomHorizontalFlip(),
                                       torchvision.transforms.AutoAugment(torchvision.transforms.AutoAugmentPolicy.IMAGENET),
                                       transforms.ToTensor(),
                                       transforms.Normalize([0.485, 0.456, 0.406],
                                                            [0.229, 0.224, 0.225])])
# Data augmentation for testing
test_transforms = transforms.Compose([transforms.Resize(255),
                                      transforms.CenterCrop(224),
                                      transforms.ToTensor(),
                                      transforms.Normalize([0.485, 0.456, 0.406],
                                                           [0.229, 0.224, 0.225])])


class Label_encoder:
    def __init__(self, labels):
        labels = list(set(labels))
        self.labels = {label: idx for idx, label in enumerate(classes)}

    def get_label(self, idx):
        return list(self.labels.keys())[idx]

    def get_idx(self, label):
        return self.labels[label]

encoder = Label_encoder(classes)
for i in range(20):
    print(encoder.get_label(i), encoder.get_idx( encoder.get_label(i) ))
```

```
apple_pie 0
baby_back_ribs 1
baklava 2
beef_carpaccio 3
beef_tartare 4
beet_salad 5
beignets 6
bibimbap 7
bread_pudding 8
breakfast_burrito 9
bruschetta 10
caesar_salad 11
cannoli 12
caprese_salad 13
carrot_cake 14
ceviche 15
cheesecake 16
cheese_plate 17
chicken_curry 18
chicken_quesadilla 19
```

```
class Food20(Dataset):
    def __init__(self, dataframe, transform=None):
        self.dataframe = dataframe
        self.transform = transform

    def __len__(self):
        return self.dataframe.shape[0]

    def __getitem__(self, idx):
        img_name = self.dataframe.path.iloc[idx]
        image = Image.open(img_name)
        if image.mode != 'RGB':
            image = image.convert('RGB')
        label = encoder.get_idx(self.dataframe.label.iloc[idx])

        if self.transform:
            image = self.transform(image)

        return image, label


train_dataset = Food20(train_imgs, transform=train_transforms)
test_dataset = Food20(test_imgs, transform=test_transforms)
train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)


for i in range(10):
    image = train_dataset.__getitem__(i)
    print(encoder.get_label(image[1]), image[0].shape)
```

```
escargots torch.Size([3, 224, 224])
lobster_roll_sandwich torch.Size([3, 224, 224])
takoyaki torch.Size([3, 224, 224])
peking_duck torch.Size([3, 224, 224])
lobster_bisque torch.Size([3, 224, 224])
pad_thai torch.Size([3, 224, 224])
hot_and_sour_soup torch.Size([3, 224, 224])
omelette torch.Size([3, 224, 224])
chicken_curry torch.Size([3, 224, 224])
foie_gras torch.Size([3, 224, 224])
```

```
weights = models.DenseNet201_Weights.IMAGENET1K_V1
model = models.densenet201(weights = weights)
```

```
Downloading: "https://download.pytorch.org/models/densenet201-c1103571.pth" to /root/.cache/torch/hub/checkpoints/densenet201-c1103
100%|██████████| 77.4M/77.4M [00:00<00:00, 101MB/s]
```

```
weights = models.DenseNet201_Weights.IMAGENET1K_V1
model = models.densenet201(weights = weights)


num_epochs = 3


loss_fn = nn.CrossEntropyLoss()

# all parameters are being optimized
optimizer = torch.optim.Adam(model.parameters(), lr=0.001, betas=[0.9, 0.999])

model = model.to(device)
```

```
def train_step(model: torch.nn.Module,
               dataloader: torch.utils.data.DataLoader,
               loss_fn: torch.nn.Module,
               optimizer: torch.optim.Optimizer,
               device: torch.device):
  # Put model in train mode
  model.train()

  # Setup train loss and train accuracy values
  train_loss, train_acc = 0, 0

  print("--> Training Progress")
  # Loop through data loader data batches
  for batch, (X, y) in enumerate(tqdm(dataloader)):
      # Send data to target device
      images, labels = X.to(device), y.to(device)

      # 1. Forward pass
      y_pred = model(images)

      # 2. Calculate  and accumulate loss
      loss = loss_fn(y_pred, labels)
      train_loss += loss.item()

      # 3. Optimizer zero grad
      optimizer.zero_grad()

      # 4. Loss backward
      loss.backward()

      # 5. Optimizer step
      optimizer.step()

      # Calculate and accumulate accuracy metric across all batches
      y_pred_class = torch.argmax(torch.softmax(y_pred, dim=1), dim=1)
      train_acc += (y_pred_class == labels).sum().item()/len(y_pred)

  # Adjust metrics to get average loss and accuracy per batch
  train_loss = train_loss / len(dataloader)
  train_acc = train_acc / len(dataloader)
  return train_loss, train_acc
```

```
!pip install torch torchvision torchaudio
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from tqdm.auto import tqdm

def test_step(model: torch.nn.Module,
              dataloader: torch.utils.data.DataLoader,
              loss_fn: torch.nn.Module,
              device: torch.device):
  # Put model in eval mode
  model.eval()

  # Setup test loss and test accuracy values
  test_loss, test_acc = 0, 0

  # Turn on inference context manager
  with torch.inference_mode():
      print("--> Testing Progress")
      # Loop through DataLoader batches
      for batch, (X, y) in enumerate(tqdm(dataloader)):
          # Send data to target device
          images, labels = X.to(device), y.to(device)

          # 1. Forward pass
          test_pred_logits = model(images)

          # 2. Calculate and accumulate loss
          loss = loss_fn(test_pred_logits, labels)
          test_loss += loss.item()

          # Calculate and accumulate accuracy
          test_pred_labels = torch.argmax(torch.softmax(test_pred_logits, dim=1), dim=1)

          test_acc += ((test_pred_labels == labels).sum().item()/len(test_pred_labels))

  # Adjust metrics to get average loss and accuracy per batch
  test_loss = test_loss / len(dataloader)
  test_acc = test_acc / len(dataloader)
  return test_loss, test_acc
```

```
equirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (2.3.0+cu121)
equirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-packages (0.18.0+cu121)
equirement already satisfied: torchaudio in /usr/local/lib/python3.10/dist-packages (2.3.0+cu121)
equirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch) (3.15.4)
equirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/python3.10/dist-packages (from torch) (4.12.2)
equirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch) (1.12.1)
equirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch) (3.3)
equirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch) (3.1.4)
equirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch) (2023.6.0)
ollecting nvidia-cuda-nvrtc-cu12==12.1.105 (from torch)
 Using cached nvidia_cuda_nvrtc_cu12-12.1.105-py3-none-manylinux1_x86_64.whl (23.7 MB)
ollecting nvidia-cuda-runtime-cu12==12.1.105 (from torch)
 Using cached nvidia_cuda_runtime_cu12-12.1.105-py3-none-manylinux1_x86_64.whl (823 kB)
ollecting nvidia-cuda-cupti-cu12==12.1.105 (from torch)
 Using cached nvidia_cuda_cupti_cu12-12.1.105-py3-none-manylinux1_x86_64.whl (14.1 MB)
ollecting nvidia-cudnn-cu12==8.9.2.26 (from torch)
 Using cached nvidia_cudnn_cu12-8.9.2.26-py3-none-manylinux1_x86_64.whl (731.7 MB)
ollecting nvidia-cublas-cu12==12.1.3.1 (from torch)
 Using cached nvidia_cublas_cu12-12.1.3.1-py3-none-manylinux1_x86_64.whl (410.6 MB)
ollecting nvidia-cufft-cu12==11.0.2.54 (from torch)
 Using cached nvidia_cufft_cu12-11.0.2.54-py3-none-manylinux1_x86_64.whl (121.6 MB)
ollecting nvidia-curand-cu12==10.3.2.106 (from torch)
 Using cached nvidia_curand_cu12-10.3.2.106-py3-none-manylinux1_x86_64.whl (56.5 MB)
ollecting nvidia-cusolver-cu12==11.4.5.107 (from torch)
 Using cached nvidia_cusolver_cu12-11.4.5.107-py3-none-manylinux1_x86_64.whl (124.2 MB)
ollecting nvidia-cusparse-cu12==12.1.0.106 (from torch)
 Using cached nvidia_cusparse_cu12-12.1.0.106-py3-none-manylinux1_x86_64.whl (196.0 MB)
ollecting nvidia-nccl-cu12==2.20.5 (from torch)
 Using cached nvidia_nccl_cu12-2.20.5-py3-none-manylinux2014_x86_64.whl (176.2 MB)
ollecting nvidia-nvtx-cu12==12.1.105 (from torch)
 Using cached nvidia_nvtx_cu12-12.1.105-py3-none-manylinux1_x86_64.whl (99 kB)
equirement already satisfied: triton==2.3.0 in /usr/local/lib/python3.10/dist-packages (from torch) (2.3.0)
ollecting nvidia-nvjitlink-cu12 (from nvidia-cusolver-cu12==11.4.5.107->torch)
 Downloading nvidia_nvjitlink_cu12-12.5.82-py3-none-manylinux2014_x86_64.whl (21.3 MB)
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21.3/21.3 MB 39.2 MB/s eta 0:00:00
equirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from torchvision) (1.25.2)
equirement already satisfied: pillow!=8.3.*,>=5.3.0 in /usr/local/lib/python3.10/dist-packages (from torchvision) (9.4.0)
equirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch) (2.1.5)
equirement already satisfied: mpmath<1.4.0,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.0)
nstalling collected packages: nvidia-nvtx-cu12, nvidia-nvjitlink-cu12, nvidia-nccl-cu12, nvidia-curand-cu12, nvidia-cufft-cu12, nvidi
uccessfully installed nvidia-cublas-cu12-12.1.3.1 nvidia-cuda-cupti-cu12-12.1.105 nvidia-cuda-nvrtc-cu12-12.1.105 nvidia-cuda-runtime
```

```
def test_step(model: torch.nn.Module
```

```
def test_step(model: torch.nn.Module,
              dataloader: torch.utils.data.DataLoader,
              loss_fn: torch.nn.Module,
              device: torch.device):
  # Put model in eval mode
  model.eval()

  # Setup test loss and test accuracy values
  test_loss, test_acc = 0, 0

  # Turn on inference context manager
  with torch.inference_mode():
      print("--> Testing Progress")
      # Loop through DataLoader batches
      for batch, (X, y) in enumerate(tqdm(dataloader)):
          # Send data to target device
          images, labels = X.to(device), y.to(device)

          # 1. Forward pass
          test_pred_logits = model(images)

          # 2. Calculate and accumulate loss
          loss = loss_fn(test_pred_logits, labels)
          test_loss += loss.item()

          # Calculate and accumulate accuracy
          test_pred_labels = torch.argmax(torch.softmax(test_pred_logits, dim=1), dim=1)

          test_acc += ((test_pred_labels == labels).sum().item()/len(test_pred_labels))

  # Adjust metrics to get average loss and accuracy per batch
  test_loss = test_loss / len(dataloader)
  test_acc = test_acc / len(dataloader)
  return test_loss, test_acc


def train(model: torch.nn.Module,
          train_dataloader: torch.utils.data.DataLoader,
          test_dataloader: torch.utils.data.DataLoader,
          optimizer: torch.optim.Optimizer,
          loss_fn: torch.nn.Module,
          epochs: int,
          device: torch.device):
  # Create empty results dictionary
  history = {
      "train_loss": [],
      "train_acc": [],
      "test_loss": [],
      "test_acc": [],
      'best train acc': (0, 0),
      "best_model": dict()
  }
```

What is Colab?

Colab, or "Colaboratory", allows you to write and execute Python in your browser, with

- Zero configuration required
- Access to GPUs free of charge
- Easy sharing

Whether you're a **student**, a **data scientist** or an **AI researcher**, Colab can make your work easier. Watch Introduction to Colab or Colab Features You May Have Missed to learn more, or just get started below!

Getting started

The document you are reading is not a static web page, but an interactive environment called a **Colab notebook** that lets you write and execute code.

For example, here is a **code cell** with a short Python script that computes a value, stores it in a variable, and prints the result:

```
seconds_in_a_day = 24 * 60 * 60
seconds_in_a_day
```

```
86400
```