∨ 데이터 준비

∨ max_length 계산

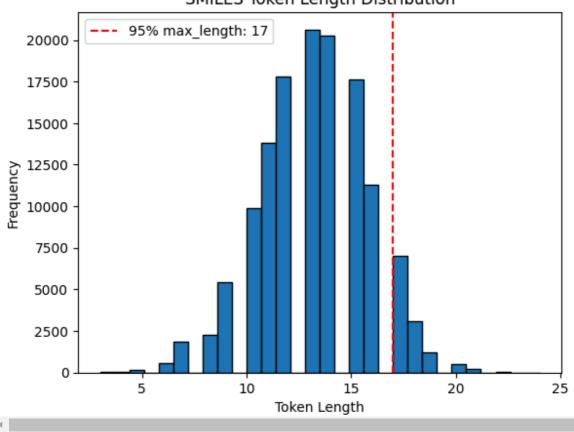
```
import pandas as pd
from transformers import RobertaTokenizer
# QM9 데이터셋 로드
file_path = "/content/gm9.csv"
qm9_data = pd.read_csv(file_path)
# ChemBERTa 토크나이저 로드
tokenizer = RobertaTokenizer.from_pretrained("seyonec/ChemBERTa-zinc-base-v1")
# 각 SMILES의 토큰 길이 계산 함수
def calculate_token_length(smiles):
   tokens = tokenizer(smiles, return_tensors="pt", padding=False, truncation=False)
   return len(tokens["input_ids"][0])
# 각 SMILES의 토큰 길이 계산 및 데이터프레임에 추가
qm9_data["token_length"] = qm9_data["smiles"].apply(calculate_token_length)
# 길이 분포 통계 확인
length_stats = gm9_data["token_length"].describe()
print("SMILES Token Length Statistics:")
print(length_stats)
# 95% 백분위수 계산
max_length_95 = int(qm9_data["token_length"].quantile(0.95))
print(f"95%의 SMILES는 {max_length_95} 토큰 이하의 길이를 가집니다.")
# 길이 분포 히스토그램 시각화 (선택적)
import matplotlib.pyplot as plt
plt.hist(gm9_data["token_length"], bins=30, edgecolor="k")
plt.axvline(max_length_95, color="r", linestyle="--", label=f"95% max_length: {max_length_95}")
plt.title("SMILES Token Length Distribution")
plt.xlabel("Token Length")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```

SMILES	Token Length Statistics
count	133885.000000
mean	13.157829
std	2.571324
min	3.000000
25%	11.000000
50%	13.000000
75%	15.000000
max	24.000000

Name: token_length, dtype: float64

95%의 SMILES는 17 토큰 이하의 길이를 가집니다.

SMILES Token Length Distribution



Canonical SMILES 변환

!pip install rdkit

→ Collecting rdkit

Downloading rdkit-2024.3.6-cp310-cp310-manylinux_2_28_x86_64.whl.metadata (4.0 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from rdkit) (1.
Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit) (1.
Downloading rdkit-2024.3.6-cp310-cp310-manylinux_2_28_x86_64.whl (32.8 MB)

______ 32.8/32.8 MB

Installing collected packages: rdkit Successfully installed rdkit-2024.3.6

non Canonical SMILES 비율 확인

from rdkit import Chem import pandas as pd

```
# QM9 데이터셋 로드
file_path = "/content/qm9.csv" # QM9 데이터 파일 경로
qm9_data = pd.read_csv(file_path)
# Canonical SMILES 확인 함수
def is_canonical(smiles):
   trv:
       mol = Chem.MolFromSmiles(smiles) # SMILES 문자열을 Mol 객체로 변환
       if mol is None:
           return False # 변환 실패
       canonical_smiles = Chem.MolToSmiles(mol, canonical=True) # Canonical SMILES 생성
       return smiles == canonical_smiles # 원본과 Canonical SMILES 비교
   except Exception as e:
       return False # 예외 발생 시 False 반환
# Canonical SMILES 여부 확인
qm9_data["is_canonical"] = qm9_data["smiles"].apply(is_canonical)
# 결과 통계
canonical_count = qm9_data["is_canonical"].sum()
non_canonical_count = len(qm9_data) - canonical_count
print(f"Total samples checked: {len(qm9_data)}")
print(f"Canonical SMILES count: {canonical_count}")
print(f"Non-canonical SMILES count: {non_canonical_count}")
Total samples checked: 133885
     Canonical SMILES count: 51287
     Non-canonical SMILES count: 82598
     Non-canonical SMILES samples have been saved to 'non_canonical_smiles.csv'.
from rdkit import Chem
import pandas as pd
# QM9 데이터셋 로드
qm9_data = pd.read_csv("/content/qm9.csv")
# Canonical SMILES 변환 함수
def convert_to_canonical(smiles):
   try:
       mol = Chem.MolFromSmiles(smiles)
       if mol is None:
           return None
       return Chem.MolToSmiles(mol, canonical=True)
   except Exception:
       return None
# 데이터셋에 Canonical SMILES 적용
qm9_data["canonical_smiles"] = qm9_data["smiles"].apply(convert_to_canonical)
# Canonical SMILES가 None인 데이터 제거
qm9_data = qm9_data.dropna(subset=["canonical_smiles"])
# 확인
```

```
print(qm9_data.head())

# Canonical SMILES 데이터셋 저장
qm9_data[["canonical_smiles", "gap"]].to_csv("qm9_canonical.csv", index=False)
```

```
homo
\rightarrow
      mol_id smiles
                                         В
                                                     C
                                                           mu alpha
                    157.71180
                                157.709970 157.706990 0.0000
                                                               13.21 -0.3877
    0 gdb_1
                 С
    1 gdb_2
                  N 293.60975 293.541110 191.393970 1.6256
                                                               9.46 -0.2570
    2 gdb_3
                  ()
                    799.58812 437.903860 282.945450 1.8511
                                                                6.31 - 0.2928
    3 gdb_4
                C#C
                      0.00000
                                 35.610036
                                            35.610036 0.0000
                                                               16.28 -0.2845
    4 gdb_5
                C#N
                       0.00000
                                 44.593883
                                            44.593883 2.8937
                                                               12.99 -0.3604
                                            u298
                                                      h298
         lumo
                                   u0
                                                                 g298
                  gap
                                                                          CV
    0 0.1171 0.5048
                       ... -40.478930 -40.476062 -40.475117 -40.498597
                                                                       6.469
    1 0.0829 0.3399 ... -56.525887 -56.523026 -56.522082 -56.544961 6.316
    2 0.0687 0.3615 ... -76.404702 -76.401867 -76.400922 -76.422349 6.002
    3 0.0506 0.3351 ... -77.308427 -77.305527 -77.304583 -77.327429 8.574
                      ... -93.411888 -93.409370 -93.408425 -93.431246 6.278
    4 0.0191 0.3796
                    u298_atom
                                h298_atom
                                            g298_atom canonical_smiles
    0 -395.999595 -398.643290 -401.014647 -372.471772
                                                                     C
    1 -276.861363 -278.620271 -280.399259 -259.338802
                                                                     N
    2 -213.087624 -213.974294 -215.159658 -201.407171
                                                                     ()
    3 -385.501997 -387.237686 -389.016047 -365.800724
                                                                   C#C
    4 -301.820534 -302.906752 -304.091489 -288.720028
                                                                   C#N
```

[5 rows x 22 columns]

▼ train/test dataset 결정

```
import pandas as pd
from sklearn.model_selection import train_test_split
# QM9 데이터 로드
file_path = "/content/qm9.csv" # QM9 데이터셋 경로
gm9 data = pd.read csv(file path)
# 필요한 열만 추출 (smiles와 gap)
data = gm9_data[['smiles', 'gap']].dropna()
# Train/Test 데이터셋 분리 (90% Train, 10% Test)
train_data, test_data = train_test_split(data, test_size=0.1, random_state=42)
# 결과 확인
print(f"Train dataset size: {train_data.shape[0]} rows")
print(f"Test dataset size: {test_data.shape[0]} rows")
# Train/Test 데이터셋 저장
train_data.to_csv("qm9_train.csv", index=False)
test_data.to_csv("qm9_test.csv", index=False)
print("Train/Test datasets have been saved as 'qm9_train.csv' and 'qm9_test.csv'.")
```

Train dataset size: 120496 rows
Test dataset size: 13389 rows

Train/Test datasets have been saved as 'qm9_train.csv' and 'qm9_test.csv'.

```
import pandas as pd
from sklearn.model_selection import train_test_split
# QM9 Canonical 데이터 로드
file_path = "/content/qm9_canonical.csv" # QM9 Canonical 데이터셋 경로
gm9_data = pd.read_csv(file_path)
# 필요한 열만 추출 (canonical_smiles와 gap)
data = qm9_data[['canonical_smiles', 'gap']].dropna()
# Train/Test 데이터셋 분리 (90% Train, 10% Test)
train_data, test_data = train_test_split(data, test_size=0.1, random_state=42)
# 결과 확인
print(f"Train dataset size: {train_data.shape[0]} rows")
print(f"Test dataset size: {test_data.shape[0]} rows")
# Train/Test 데이터셋 저장
train_data.to_csv("qm9_canonical_train.csv", index=False)
test_data.to_csv("qm9_canonical_test.csv", index=False)
print("Train/Test datasets have been saved as 'qm9_canonical_train.csv' and 'qm9_canonical_test.csv'."
Train dataset size: 120496 rows
     Test dataset size: 13389 rows
     Train/Test datasets have been saved as 'qm9_canonical_train.csv' and 'qm9_canonical_test.csv'.
```

Training / Testing

(Non-canonical) SMILES

```
from transformers import RobertaTokenizer, RobertaForSequenceClassification, Trainer, TrainingArgumer import torch
from torch.utils.data import Dataset
from sklearn.model_selection import train_test_split
import pandas as pd

# 모델 및 토크나이저 로드
model_name = "seyonec/ChemBERTa-zinc-base-v1"
tokenizer = RobertaTokenizer.from_pretrained(model_name)
model = RobertaForSequenceClassification.from_pretrained(model_name, num_labels=1)

# 데이터 로드
train_data = pd.read_csv("/content/qm9_train.csv")
test_data = pd.read_csv("/content/qm9_test.csv")

# SMILES 토큰화
class SMILESDataset(Dataset):
```

```
def __init__(self, dataframe, tokenizer, target_col):
       self.data = dataframe
       self.tokenizer = tokenizer
       self.target_col = target_col
   def __len__(self):
        return len(self.data)
   def __getitem__(self, idx):
       smiles = self.data.iloc[idx]['smiles']
        target = self.data.iloc[idx][self.target_col]
        tokens = self.tokenizer(smiles, padding='max_length', truncation=True, max_length=20, return_
        item = {key: val.squeeze(0) for key, val in tokens.items()}
        item['labels'] = torch.tensor(target, dtype=torch.float)
        return item
# 데이터셋 준비
train_dataset = SMILESDataset(train_data, tokenizer, 'gap')
test_dataset = SMILESDataset(test_data, tokenizer, 'gap')
# 데이터 Collator
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
# 학습 파라미터
training_args = TrainingArguments(
   output_dir='./results',
   evaluation_strategy="epoch",
    learning_rate=5e-5,
   per_device_train_batch_size=16, # 배치 크기 축소
   per_device_eval_batch_size=16,
   num_train_epochs=2, # 에포크 수
   weight_decay=0.01,
   logging_dir='./logs',
   logging_steps=10,
)
# Trainer 설정
trainer = Trainer(
   model=model,
   args=training_args,
   train_dataset=train_dataset,
   eval_dataset=test_dataset,
   data_collator=data_collator,
)
# 모델 학습
trainer.train()
# 모델 저장
model.save_pretrained("./jjh/ChemBERTa-smiles-gap")
tokenizer.save_pretrained("./jjh/ChemBERTa-smiles-gap")
print("파인튜닝 완료 및 모델 저장 완료!")
# 테스트 데이터 평가
evaluation_results = trainer.evaluate()
```

print("테스트 데이터 평가 결과:", evaluation_results)

→ Some weights of RobertaForSequenceClassification were not initialized from the model checkpoint You should probably TRAIN this model on a down-stream task to be able to use it for predictions /usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1568: FutureWarning: `eval warnings.warn(

wandb: WARNING The `run_name` is currently set to the same value as `TrainingArguments.output_d wandb: Using wandb-core as the SDK backend. Please refer to https://wandb.me/wandb-core for mo wandb: Logging into wandb.ai. (Learn how to deploy a W&B server locally: https://wandb.me/wandb wandb: You can find your API key in your browser here: https://wandb.ai/authorize

wandb: Paste an API key from your profile and hit enter, or press ctrl+c to guit: · · · wandb: Appending key for api.wandb.ai to your netrc file: /root/.netrc

Tracking run with wandb version 0.18.7

Run data is saved locally in /content/wandb/run-20241208_011606-26afhwwb

Syncing run ./results to Weights & Biases (docs)

View project at https://wandb.ai/jangjh1907-korea-university/huggingface

View run at https://wandb.ai/jangjh1907-korea-university/huggingface/runs/26afhwwb

[15062/15062 9:15:11, Epoch 2/2] Epoch Training Loss Validation Loss 1 0.000800 0.000521 2 0.000300 0.000344 파인튜닝 완료 및 모델 저장 완료!

[837/837 09:16]

테스트 데이터 평가 결과: {'eval_loss': 0.000344324012985453, 'eval_runtime': 557.5386, 'eval_sam

Canonical SMILES

```
from transformers import RobertaTokenizer, RobertaForSequenceClassification, Trainer, TrainingArgumer
import torch
from torch.utils.data import Dataset
from sklearn.model_selection import train_test_split
import pandas as pd
# 모델 및 토크나이저 로드
model_name = "seyonec/ChemBERTa-zinc-base-v1"
tokenizer = RobertaTokenizer.from_pretrained(model_name)
model = RobertaForSequenceClassification.from_pretrained(model_name, num_labels=1)
# 데이터 로드
train_data = pd.read_csv("/content/qm9_canonical_train.csv")
test_data = pd.read_csv("/content/qm9_canonical_test.csv")
# SMILES 토큰화
class SMILESDataset(Dataset):
   def __init__(self, dataframe, tokenizer, target_col):
       self.data = dataframe
       self.tokenizer = tokenizer
       self.target_col = target_col
```

```
def __len__(self):
       return len(self.data)
   def __getitem__(self, idx):
       smiles = self.data.iloc[idx]['canonical_smiles']
       target = self.data.iloc[idx][self.target_col]
       tokens = self.tokenizer(smiles, padding='max_length', truncation=True, max_length=20, return_
       item = {key: val.squeeze(0) for key, val in tokens.items()}
       item['labels'] = torch.tensor(target, dtype=torch.float)
       return item
# 데이터셋 준비 (전체 데이터 사용)
train_dataset = SMILESDataset(train_data, tokenizer, 'gap')
test_dataset = SMILESDataset(test_data, tokenizer, 'gap')
# 데이터 Collator
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
# 학습 파라미터
training_args = TrainingArguments(
   output_dir='./results'.
   evaluation_strategy="epoch",
   learning_rate=5e-5,
   per_device_train_batch_size=16, # 배치 크기
   per_device_eval_batch_size=16,
   num_train_epochs=2, # 에포크 수
   weight_decay=0.01,
   logging_dir='./logs',
   logging_steps=10,
)
# Trainer 설정
trainer = Trainer(
   model=model,
   args=training_args,
   train_dataset=train_dataset,
   eval_dataset=test_dataset,
   data_collator=data_collator,
)
# 모델 학습
trainer.train()
# 모델 저장
model.save_pretrained("./jjh/ChemBERTa-canonical_smiles-gap")
tokenizer.save_pretrained("./jjh/ChemBERTa-canonical_smiles-gap")
print("파인튜닝 완료 및 모델 저장 완료!")
# 테스트 데이터 평가
evaluation_results = trainer.evaluate()
print("테스트 데이터 평가 결과:", evaluation_results)
```



Some weights of RobertaForSequenceClassification were not initialized from the model checkpoint You should probably TRAIN this model on a down-stream task to be able to use it for predictions /usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1568: FutureWarning: `eval warnings.warn(

wandb: WARNING The `run_name` is currently set to the same value as `TrainingArguments.output_d wandb: Using wandb-core as the SDK backend. Please refer to https://wandb.me/wandb-core for mo wandb: Logging into wandb.ai. (Learn how to deploy a W&B server locally: https://wandb.me/wandb

wandb: You can find your API key in your browser here: https://wandb.ai/authorize

wandb: Paste an API key from your profile and hit enter, or press ctrl+c to quit: · ·

wandb: Appending key for api.wandb.ai to your netrc file: /root/.netrc

Tracking run with wandb version 0.18.7

Run data is saved locally in /content/wandb/run-20241208_011624-0r7ughyv

Syncing run ./results to Weights & Biases (docs)

View project at https://wandb.ai/jangjh1907-korea-university/huggingface

View run at https://wandb.ai/jangjh1907-korea-university/huggingface/runs/0r7ughyv [15062/15062 8:34:45, Epoch 2/2]

Epoch Training Loss Validation Loss 1 0.001000 0.001319 2 0.000400 0.000296

파인튜닝 완료 및 모델 저장 완료!

[837/837 08:02]

테스트 데이터 평가 결과: {'eval_loss': 0.0002959519624710083, 'eval_runtime': 483.0734, 'eval_sa

> 기타코드

[] 나 숨겨진 셀 7개