Autoencoder Cheat Sheet

AI/ML · Quick Reference

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OVERVIEW & SETUP

Autoencoder AI/ML framework

```
pip install autoencoder
# Verify installation
python -c "import autoencoder;
print('OK')"
# GPU support check
import torch;
print(torch.cuda.is_available())",
```

Use virtual environment: python -m
venv venv

DATA PREPARATION

```
import pandas as pd
df = pd.read_csv('data.csv')
X = df.drop('target', axis=1).values
y = df['target'].values
from sklearn.model_selection import
train_test_split
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2)
```

Normalize/standardize features for
best results

MODEL DEFINITION

```
# Simple neural network:
import torch.nn as nn
class Model(nn.Module):
def __init__(self):
super().__init__()
self.layers = nn.Sequential(
nn.Linear(input_size, 128),
nn.ReLU(),
nn.Linear(128, num_classes)
)
def forward(self, x): return
self.layers(x)
```

EVALUATION

```
from sklearn.metrics import
accuracy_score, classification_report
model.eval()
with torch.no_grad():
preds = model(X_test)
accuracy = accuracy_score(y_test,
preds.argmax(1))
print(classification_report(y_test,
preds.argmax(1)))
```

Track precision, recall, F1; use
confusion matrix

INFERENCE & SERVING

```
# Save model
torch.save(model.state_dict(),
'model.pt')
# Load model
model.load_state_dict(torch.load('model.pt'))
model.eval()
# Inference
with torch.no_grad():
prediction = model(input_tensor)
```

HYPERPARAMETERS

Learning rate: start with 1e-3, tune
with scheduler
Batch size: 32-256 depending on GPU
memory
Epochs: use early stopping to
prevent overfitting

```
scheduler =
torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer)
scheduler.step(val_loss)
```

Grid search or Optuna for systematic
tuning

DATASETS & LOADERS

```
from torch.utils.data import Dataset,
DataLoader
class MyDataset(Dataset):
def __len__(self): return len(self.data)
def __getitem__(self, idx): return
self.data[idx]
loader = DataLoader(dataset,
batch_size=32, shuffle=True,
num_workers=4)
```

Pin memory for faster GPU data
transfer

OPTIMIZATION TECHNIQUES

Mixed precision:
torch.cuda.amp.autocast()",
Gradient clipping:
clip_grad_norm_(model.parameters(),
1.0)",
Batch normalization:
nn.BatchNorm1d()",
Dropout: nn.Dropout(0.5) for
regularization",

```
# Learning rate warmup
from transformers import
get_linear_schedule_with_warmup
```

FRAMEWORKS & TOOLS

TensorFlow / Keras	production ML
PyTorch	research & NLP
Scikit-learn	classical ML
Hugging Face transformers	pretrained
MLflow / W&B tracking	experiment
ONNX export/portability	model

DEPLOYMENT

```
# Export to ONNX
torch.onnx.export(model, dummy_input,
'model.onnx')
# FastAPI serving example
@app.post('/predict')
def predict(data: InputData):
tensor = preprocess(data)
return model(tensor).tolist()
```

Use TorchServe, BentoML, or Triton
for production

COMMON GOTCHAS

Gradient explosion: use gradient
clipping",
Memory leak: always zero_grad()
before backward()",
Train/eval mode: model.train() vs
model.eval()",
GPU-CPU mismatch: ensure all tensors
on same device",
Data leakage: split before
normalization, not after",