Project Discription:

Dataset: https://github.com/ant-research/EasyTemporalPointProcess

Model Method: https://arxiv.org/abs/1705.08982

Install EasyTPP and Data Loading

```
!pip install git+https://github.com/ant-research/EasyTemporalPointProcess.git
```

```
Collecting git+https://github.com/ant-research/EasyTemporalPointProcess.git
  Cloning https://github.com/ant-research/EasyTemporalPointProcess.git to /tmp/pip-req-build-ay3k915g
  Running command git clone --filter=blob:none --quiet https://github.com/ant-research/EasyTemporalPointProcess.git /tmp/pip-req-build-ay3k915g
  Resolved https://github.com/ant-research/EasyTemporalPointProcess.git to commit e27440645e2278a6d20aa0d0bdec3ee53aaf91d5
  Preparing metadata (setup.py) ... done
Requirement already satisfied: PyYAML>=5.1 in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (6.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (1.26.4)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (2.2.2)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (2.5.1+cu121)
Requirement already satisfied: tensorboard in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (2.17.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (24.2)
Requirement already satisfied: datasets in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (3.1.0)
Requirement already satisfied: omegaconf in /usr/local/lib/python3.10/dist-packages (from easy_tpp==0.0.8) (2.3.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (3.16.1)
Requirement already satisfied: pyarrow>=15.0.0 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (17.0.0)
Requirement already satisfied: dill<0.3.9,>=0.3.0 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (0.3.8)
Requirement already satisfied: requests>=2.32.2 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (2.32.3)
Requirement already satisfied: tqdm>=4.66.3 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (4.66.6)
Requirement already satisfied: xxhash in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (3.5.0)
Requirement already satisfied: multiprocess<0.70.17 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (0.70.16)
Requirement already satisfied: fsspec<=2024.9.0,>=2023.1.0 in /usr/local/lib/python3.10/dist-packages (from fsspec[http]<=2024.9.0,>=2023.1.0->data
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (3.11.2)
Requirement already satisfied: huggingface-hub>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from datasets->easy_tpp==0.0.8) (0.26.2)
Requirement already satisfied: antlr4-python3-runtime==4.9.* in /usr/local/lib/python3.10/dist-packages (from omegaconf->easy_tpp==0.0.8) (4.9.3)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas->easy_tpp==0.0.8) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->easy_tpp==0.0.8) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas->easy_tpp==0.0.8) (2024.2)
Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (1.4.0)
Requirement already satisfied: grpcio>=1.48.2 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (1.68.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (3.7)
Requirement already satisfied: protobuf!=4.24.0,>=3.19.6 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (4.25.5)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (75.1.0)
Requirement already satisfied: six>1.9 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (1.16.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard->easy_tpp==0.0.8) (3.1.3)
Requirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/python3.10/dist-packages (from torch->easy_tpp==0.0.8) (4.12.2)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch->easy_tpp==0.0.8) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch->easy_tpp==0.0.8) (3.1.4)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-packages (from torch->easy_tpp==0.0.8) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch->easy_tpp==0.0.8) (1.3.0)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (2.4.3)
Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (1.3.1)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (24.2.0)
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (1.5.0)
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (6.1.0)
Requirement already satisfied: propcache>=0.2.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (0.2.0)
Requirement already satisfied: yarl<2.0,>=1.17.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (1.17.2)
Requirement already satisfied: async-timeout<6.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets->easy_tpp==0.0.8) (4.0.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets->easy_tpp==0.0.
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets->easy_tpp==0.0.8) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets->easy_tpp==0.0.8) (2.
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets->easy_tpp==0.0.8) (20
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1->tensorboard->easy_tpp==0.0.8) (3
```

```
from datasets import load_dataset

# we choose taxi dataset as it is relatively small
dataset = load_dataset('easytpp/taxi')
```

Show hidden output

```
dataset
```

```
DatasetDict({
    train: Dataset({
        features: ['seq_len', 'time_since_start', 'seq_idx', 'time_since_last_event', 'type_event', 'dim_process'],
        num_rows: 1400
    })
    validation: Dataset({
        features: ['seq_len', 'time_since_start', 'seq_idx', 'time_since_last_event', 'type_event', 'dim_process'],
        num_rows: 200
    })
    test: Dataset({
        features: ['seq_len', 'time_since_start', 'seq_idx', 'time_since_last_event', 'type_event', 'dim_process'],
        num_rows: 400
    })
})
```

```
dataset['train']['type_event'][0]
```

Show hidden output

```
#As an illustrative example, we write the YAML content to a file
yaml_content = """
pipeline_config_id: data_config

data_format: json
train_dir: easytpp/taxi  # ./data/taxi/train.json
valid_dir: easytpp/taxi  # ./data/taxi/dev.json
test_dir: easytpp/taxi   # ./data/taxi/test.json
data_specs:
  num_event_types: 10
  pad_token_id: 10
  padding_side: right
"""

# Save the content to a file named config.yaml
```

```
with open("config.yaml", "w") as file:
    file.write(yaml_content)
```

```
from easy_tpp.config_factory import Config
from easy_tpp.preprocess.data_loader import TPPDataLoader


config = Config.build_from_yaml_file('./config.yaml')
tpp_loader = TPPDataLoader(config)
```

```
2024-12-01 20:20:11,248 - config.py[pid:4048;line:34:build_from_yaml_file] - CRITICAL: Load pipeline config class DataConfig
```

Dataset Statistics

```
stats = tpp_loader.get_statistics(split='train')
stats
```

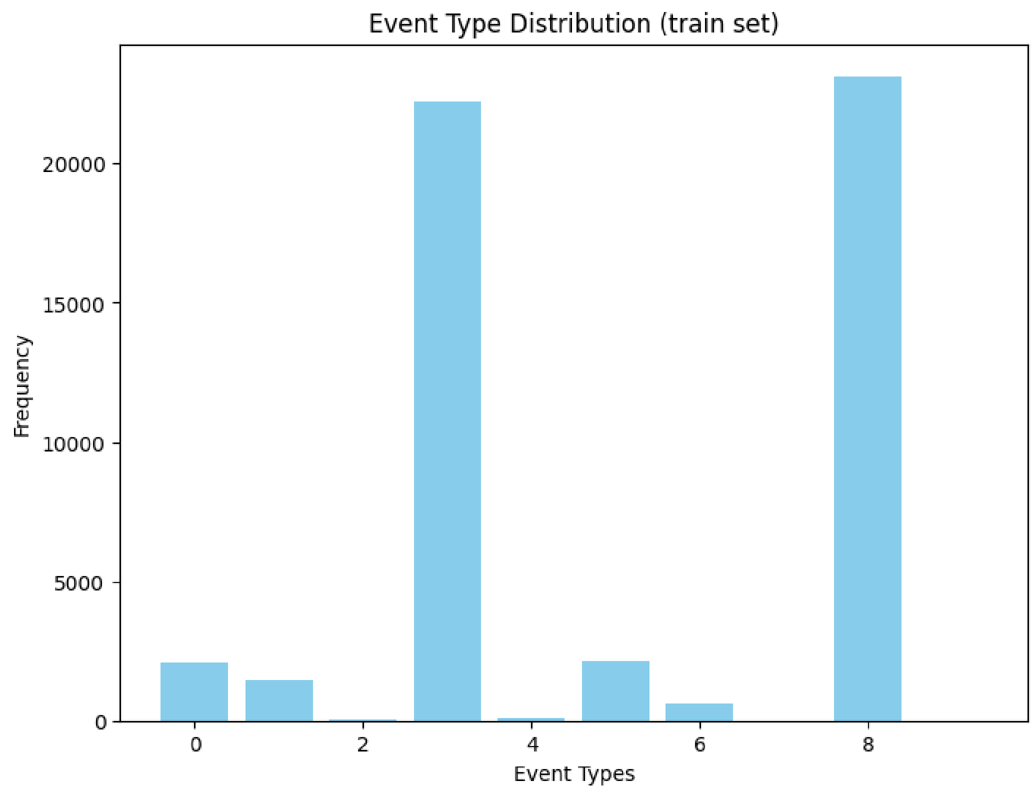
```
{'num_sequences': 1400,
 'avg_sequence_length': 37.03857142857143,
 'event_type_distribution': {8: 23131,
  3: 22239,
  5: 2161,
  0: 2088,
  1: 1443,
  6: 625,
  4: 107,
  2: 50,
  9: 4,
  7: 6},
 'max_sequence_length': 38,
 'min_sequence_length': 36,
 'mean_time_delta': 0.21851826495759416,
 'min_time_delta': 0.0,
 'max_time_delta': 5.721388888888889}
```

```
stats_test = tpp_loader.get_statistics(split='test')
stats_test
```

```
{'num_sequences': 400,
 'avg_sequence_length': 37.05,
 'event_type_distribution': {8: 6648,
  3: 6395,
  1: 399,
  0: 562,
  5: 555,
  4: 38,
  6: 202,
  9: 2,
  7: 3,
  2: 16},
 'max_sequence_length': 38,
 'min_sequence_length': 36,
 'mean_time_delta': 0.21560524441445447,
 'min_time_delta': 0.0,
 'max_time_delta': 5.246944444444444}
```

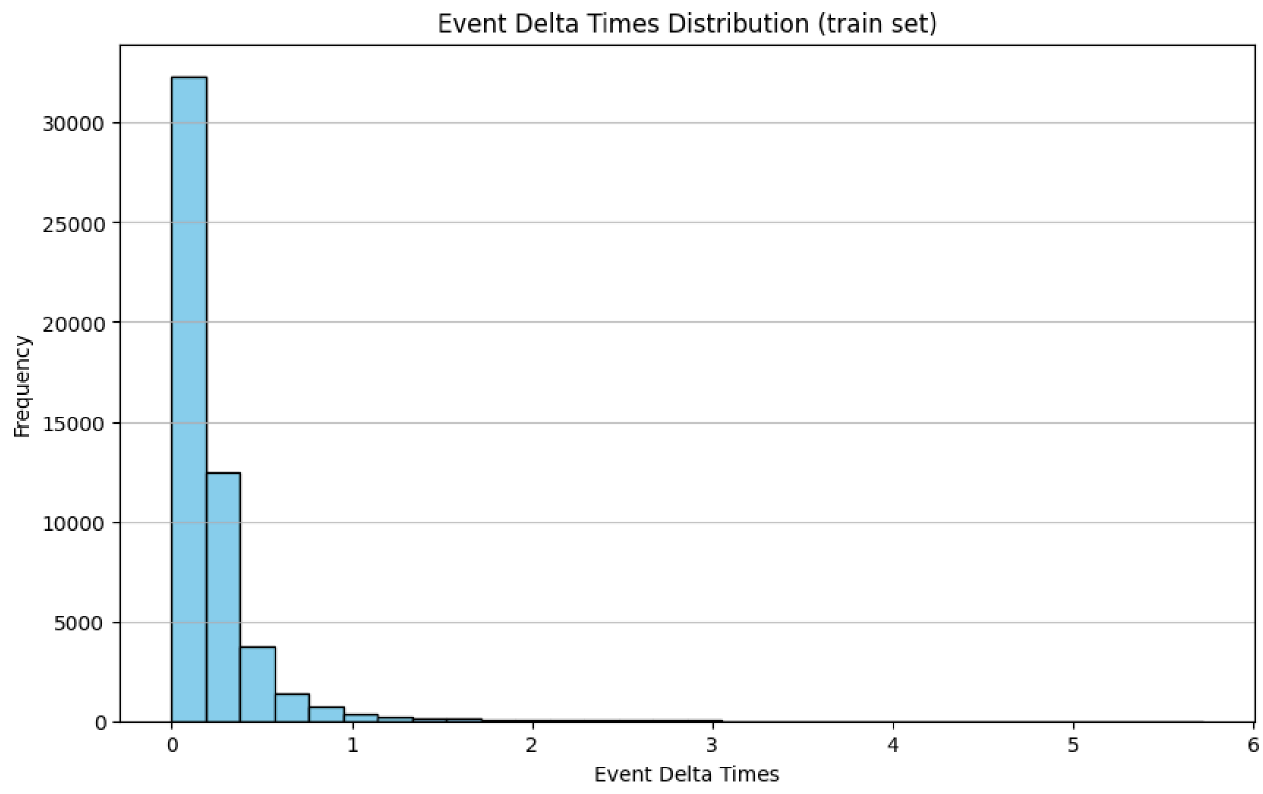
Event Type Distribution Plot

```
tpp_loader.plot_event_type_distribution()
```



Event Delta Time Distribution Plot

```
tpp_loader.plot_event_delta_times_distribution()
```



Model

version 1

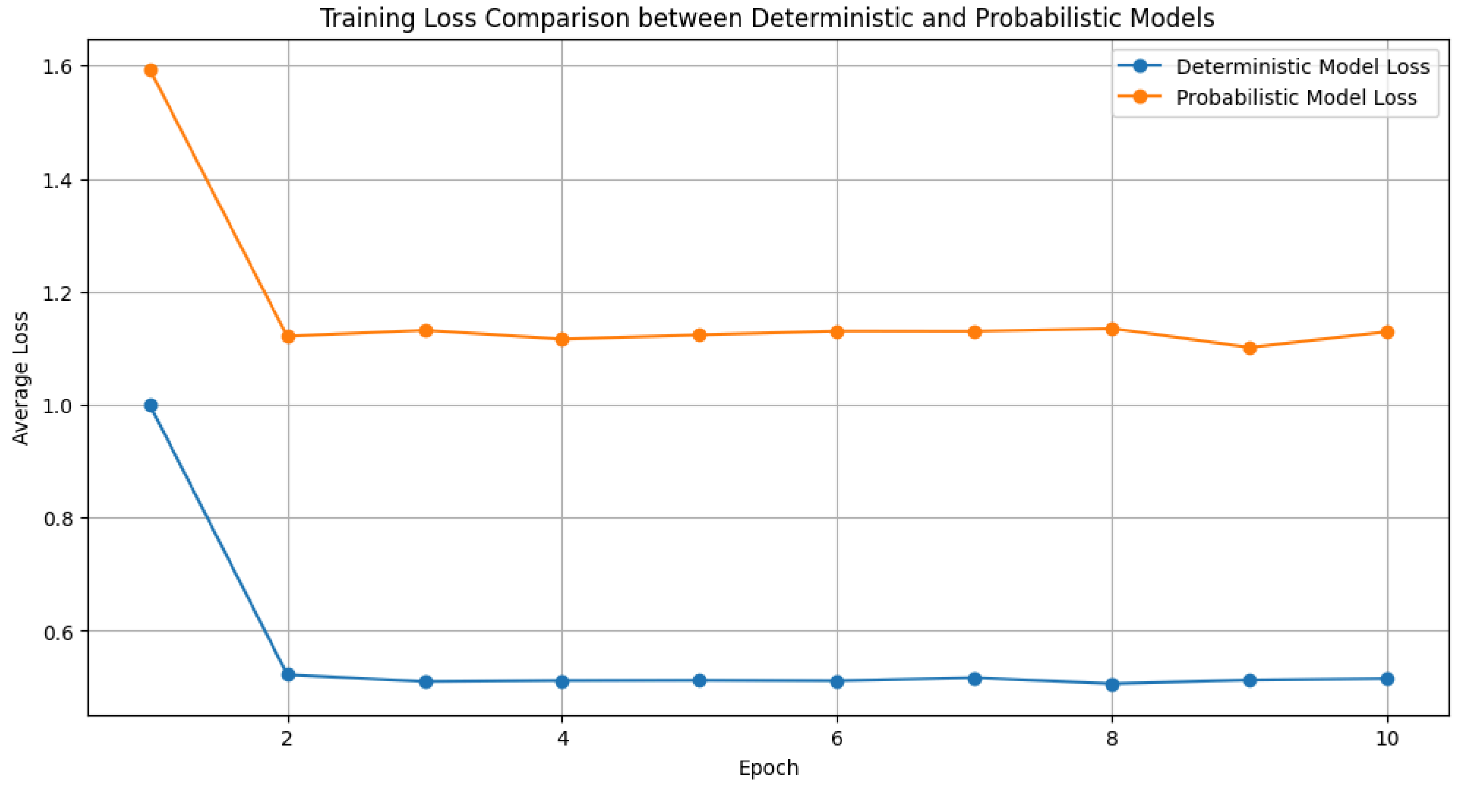
```
# Convert 'time_since_last_event' to tensors and pad sequences
x_times_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.float32) for seq in dataset['train']['time_since_last_event']],
    batch_first=True,
    padding_value=0.0  # Padding value for time differences
).to('cpu')  # Use 'cpu' or 'cuda' depending on your device

# Convert 'type_event' to tensors and pad sequences
y_events_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.long) for seq in dataset['train']['type_event']],
    batch_first=True,
    padding_value=9  # Assuming event_class = 10; use (event_class - 1) for padding
).to('cpu')  # Use 'cpu' or 'cuda' depending on your device


# Create a TensorDataset and DataLoader with the loaded real dataset
train_dataset = TensorDataset(x_times_train_padded, y_events_train_padded)
dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)
```

```
import torch
from torch import nn
from torch.optim import Adam
import numpy as np
import matplotlib.pyplot as plt
from torch.optim.lr_scheduler import StepLR
from torch.utils.data import DataLoader, TensorDataset
from datasets import load_dataset
from torch.nn.utils.rnn import pad_sequence


# Set device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class PointProcessNet(nn.Module):
    def __init__(self, config, lossweight, probabilistic=False):
        super(PointProcessNet, self).__init__()
        self.config = config
        self.probabilistic = probabilistic
        self.n_class = config.event_class
        self.embedding = nn.Embedding(num_embeddings=config.event_class, embedding_dim=config.emb_dim)
        self.emb_drop = nn.Dropout(p=config.dropout)
        self.lstm = nn.LSTM(input_size=config.emb_dim + 1,
                            hidden_size=config.hid_dim,
                            batch_first=True,
                            bidirectional=False)
        self.mlp = nn.Linear(in_features=config.hid_dim, out_features=config.mlp_dim)
        self.mlp_drop = nn.Dropout(p=config.dropout)
        self.event_linear = nn.Linear(in_features=config.mlp_dim, out_features=config.event_class)
        self.time_linear = nn.Linear(in_features=config.mlp_dim, out_features=1)
        self.set_criterion(lossweight)

    def set_optimizer(self):
        self.optimizer = Adam(params=self.parameters(), lr=self.config.lr)
        self.scheduler = StepLR(self.optimizer, step_size=100, gamma=0.1)

    def set_criterion(self, weight):
        self.event_criterion = nn.CrossEntropyLoss(weight=torch.FloatTensor(weight).to(device))
        if self.probabilistic:
            self.intensity_w = nn.Parameter(torch.tensor(0.1, dtype=torch.float, device=device))
            self.intensity_b = nn.Parameter(torch.tensor(0.1, dtype=torch.float, device=device))
            self.time_criterion = self.probabilistic_loss
        else:
            self.time_criterion = nn.MSELoss()

    def probabilistic_loss(self, pred, gold):
        # Introducing a probabilistic approach for loss, similar to RMTPP but with stochastic components
        mean_pred = torch.mean(pred)
        variance_pred = torch.var(pred) + 1e-6  # Adding a small value to prevent zero variance
```

```
        gaussian_dist = torch.distributions.Normal(mean_pred, variance_pred.sqrt())
        log_prob = gaussian_dist.log_prob(gold)
        loss = -torch.mean(log_prob)
        return loss

    def forward(self, input_time, input_events):
        event_embedding = self.embedding(input_events)
        event_embedding = self.emb_drop(event_embedding)
        lstm_input = torch.cat((event_embedding, input_time.unsqueeze(-1)), dim=-1)
        hidden_state, _ = self.lstm(lstm_input)

        mlp_output = torch.tanh(self.mlp(hidden_state[:, -1, :]))
        mlp_output = self.mlp_drop(mlp_output)
        event_logits = self.event_linear(mlp_output)
        time_logits = self.time_linear(mlp_output)

        if self.probabilistic:
            # Apply a probabilistic component to time prediction using reparameterization trick
            time_mean = time_logits
            time_log_var = torch.log(1 + torch.exp(time_logits))
            epsilon = torch.randn_like(time_log_var)
            time_logits = time_mean + epsilon * torch.exp(0.5 * time_log_var)

        return time_logits, event_logits

    def dispatch(self, tensors):
        for i in range(len(tensors)):
            tensors[i] = tensors[i].to(device).contiguous()
        return tensors

    def train_batch(self, batch):
        self.train()
        time_tensor, event_tensor = batch
        time_input, time_target = self.dispatch([time_tensor[:, :-1], time_tensor[:, -1]])
        event_input, event_target = self.dispatch([event_tensor[:, :-1], event_tensor[:, -1]])

        self.optimizer.zero_grad()
        time_logits, event_logits = self.forward(time_input, event_input)
        loss1 = self.time_criterion(time_logits.view(-1), time_target.view(-1))
        loss2 = self.event_criterion(event_logits.view(-1, self.n_class), event_target.view(-1))
        loss = self.config.alpha * loss1 + loss2
        loss.backward()

        self.optimizer.step()
        self.scheduler.step()
        return loss1.item(), loss2.item(), loss.item()

    def predict(self, batch):
        self.eval()
        time_tensor, event_tensor = batch
        time_input, time_target = self.dispatch([time_tensor[:, :-1], time_tensor[:, -1]])
        event_input, event_target = self.dispatch([event_tensor[:, :-1], event_tensor[:, -1]])
        with torch.no_grad():
            time_logits, event_logits = self.forward(time_input, event_input)
        event_pred = np.argmax(event_logits.detach().cpu().numpy(), axis=-1)
        time_pred = time_logits.detach().cpu().numpy()
        return time_pred, event_pred

# Configuration for Taxi Dataset
class Config:
    def __init__(self):
        self.event_class = 10
        self.emb_dim = 32
        self.hid_dim = 64
        self.mlp_dim = 64
        self.dropout = 0.2
        self.lr = 0.001
        self.alpha = 0.5
        self.model = 'deterministic'

config = Config()

# Instantiate deterministic and probabilistic models
deterministic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=False).to(device)
probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to(device)

# # Instantiate and train the deterministic model
# config = Config()
# deterministic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=False).to('cpu')
# probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to('cpu')
# Call set_optimizer for both models
deterministic_model.set_optimizer(total_step=len(dataloader), use_bert=False) # This line was missing
probabilistic_model.set_optimizer(total_step=len(dataloader), use_bert=False)

# Load the dataset from HuggingFace
dataset = load_dataset('easytpp/taxi')

# Extract features from the train split using the correct column names
#x_times_train = torch.tensor(dataset['train']['time_since_last_event'], dtype=torch.float32).to(device)
x_times_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.float32) for seq in dataset['train']['time_since_last_event']],
    batch_first=True,
    padding_value=0.0  # Choose an appropriate padding value
).to(device)
#x_times_train = x_times_train_padded.unsqueeze(-1)
#y_events_train = torch.tensor(dataset['train']['type_event'], dtype=torch.long).to(device)
y_events_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.long) for seq in dataset['train']['type_event']],
    batch_first=True,
    padding_value=config.event_class -1
).to(device)

# Create a TensorDataset and DataLoader with the loaded real dataset
train_dataset = TensorDataset(x_times_train_padded, y_events_train_padded)
dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)
```

```
# Training Loop for Deterministic Model
deterministic_losses = []
print("Training Deterministic Model")
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = deterministic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    deterministic_losses.append(avg_loss)
    print(f"Epoch [{epoch+1}/10], Loss: {avg_loss:.4f}")

# Training Loop for Probabilistic Model
probabilistic_losses = []
print("\nTraining Probabilistic Model")
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = probabilistic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    probabilistic_losses.append(avg_loss)
    print(f"Epoch [{epoch+1}/10], Loss: {avg_loss:.4f}")

# Example prediction for both models
with torch.no_grad():
    for batch in dataloader:
        print("\nDeterministic Model Predictions:")
        time_pred, event_pred = deterministic_model.predict(batch)
        print("Time Predictions:", time_pred)
        print("Event Predictions:", event_pred)

        print("\nProbabilistic Model Predictions:")
        time_pred, event_pred = probabilistic_model.predict(batch)
        print("Time Predictions:", time_pred)
        print("Event Predictions:", event_pred)
        break  # Only show predictions for the first batch

# Data Visualization
plt.figure(figsize=(12, 6))
plt.plot(range(1, 11), deterministic_losses, label='Deterministic Model Loss', marker='o')
plt.plot(range(1, 11), probabilistic_losses, label='Probabilistic Model Loss', marker='o')
plt.xlabel('Epoch')
plt.ylabel('Average Loss')
plt.title('Training Loss Comparison between Deterministic and Probabilistic Models')
plt.legend()
plt.grid(True)
plt.show()
```

```
Training Deterministic Model
Epoch [1/10], Loss: 0.9997
Epoch [2/10], Loss: 0.5225
Epoch [3/10], Loss: 0.5100
Epoch [4/10], Loss: 0.5118
Epoch [5/10], Loss: 0.5122
Epoch [6/10], Loss: 0.5114
Epoch [7/10], Loss: 0.5169
Epoch [8/10], Loss: 0.5061
Epoch [9/10], Loss: 0.5128
Epoch [10/10], Loss: 0.5153

Training Probabilistic Model
Epoch [1/10], Loss: 1.5937
Epoch [2/10], Loss: 1.1210
Epoch [3/10], Loss: 1.1315
Epoch [4/10], Loss: 1.1159
Epoch [5/10], Loss: 1.1233
Epoch [6/10], Loss: 1.1301
Epoch [7/10], Loss: 1.1298
Epoch [8/10], Loss: 1.1347
Epoch [9/10], Loss: 1.1015
Epoch [10/10], Loss: 1.1287

Deterministic Model Predictions:
Time Predictions: [[ 0.23588645]
 [ 0.23370199]
 [ 0.23509859]
 [-0.01894591]
 [-0.01978017]
 [ 0.23788702]
 [ 0.23410775]
 [ 0.23890202]
 [-0.01903649]
 [-0.01918978]
 [ 0.00056435]
 [-0.00815637]
 [ 0.2357909 ]
 [-0.01898612]
 [ 0.24004504]
 [-0.01902844]]
Event Predictions: [3 3 3 9 9 3 3 3 9 9 9 9 3 9 3 9]

Probabilistic Model Predictions:
Time Predictions: [[-0.30724376]
 [-1.2885206 ]
 [-3.8907216 ]
 [ 1.5242317 ]
 [-0.30257732]
 [-0.02018   ]
 [-2.7080963 ]
 [ 0.4106838 ]
 [ 1.0537289 ]
 [-0.3206861 ]
 [-0.0403738 ]
 [-1.8988272 ]
 [-1.8279098 ]
 [ 0.90971434]
 [ 1.5045369 ]
 [-1.2579412 ]]
Event Predictions: [3 3 3 9 9 3 3 3 9 9 9 9 3 9 3 9]
```



version 2 with slightly changes

```
import torch
from torch import nn
from torch.optim import Adam
import numpy as np
import matplotlib.pyplot as plt
from torch.optim.lr_scheduler import StepLR
from torch.utils.data import DataLoader, TensorDataset
from datasets import load_dataset
from torch.nn.utils.rnn import pad_sequence

# Set device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class PointProcessNet(nn.Module):
    def __init__(self, config, lossweight, probabilistic=False):
        super(PointProcessNet, self).__init__()
        self.config = config
        self.probabilistic = probabilistic
        self.n_class = config.event_class
```

```
        self.embedding = nn.Embedding(num_embeddings=config.event_class, embedding_dim=config.emb_dim)
        self.emb_drop = nn.Dropout(p=config.dropout)
        self.lstm = nn.LSTM(input_size=config.emb_dim + 1,
                            hidden_size=config.hid_dim,
                            batch_first=True,
                            bidirectional=False)
        self.mlp = nn.Linear(in_features=config.hid_dim, out_features=config.mlp_dim)
        self.mlp_drop = nn.Dropout(p=config.dropout)
        self.event_linear = nn.Linear(in_features=config.mlp_dim, out_features=config.event_class)

        # 时间间隔预测（均值和方差）
        self.fc_time_mean = nn.Linear(in_features=config.mlp_dim, out_features=1)  # 均值
        self.fc_time_logvar = nn.Linear(in_features=config.mlp_dim, out_features=1)  # 对数方差

        self.time_linear = nn.Linear(in_features=config.mlp_dim, out_features=1)
        self.set_criterion(lossweight)

    def set_optimizer(self, total_step, use_bert=True):
        self.optimizer = Adam(params=self.parameters(), lr=self.config.lr)
        self.scheduler = StepLR(self.optimizer, step_size=100, gamma=0.1)

    def set_criterion(self, weight):
        self.event_criterion = nn.CrossEntropyLoss(weight=torch.FloatTensor(weight).to(device))
        if self.probabilistic:
            self.intensity_w = nn.Parameter(torch.tensor(0.1, dtype=torch.float, device=device))
            self.intensity_b = nn.Parameter(torch.tensor(0.1, dtype=torch.float, device=device))
            self.time_criterion = self.probabilistic_loss
        else:
            self.time_criterion = nn.MSELoss()

    def probabilistic_loss(self, pred, gold):
        # Introducing a probabilistic approach for loss, similar to RMTPP but with stochastic components
        mean_pred = torch.mean(pred)
        variance_pred = torch.var(pred) + 1e-6  # Adding a small value to prevent zero variance
        gaussian_dist = torch.distributions.Normal(mean_pred, variance_pred.sqrt())
        log_prob = gaussian_dist.log_prob(gold)
        loss = -torch.mean(log_prob)
        return loss

    def forward(self, input_time, input_events):
        event_embedding = self.embedding(input_events)
        event_embedding = self.emb_drop(event_embedding)
        lstm_input = torch.cat((event_embedding, input_time.unsqueeze(-1)), dim=-1)
        hidden_state, _ = self.lstm(lstm_input)

        mlp_output = torch.tanh(self.mlp(hidden_state[:, -1, :]))
        mlp_output = self.mlp_drop(mlp_output)
        event_logits = self.event_linear(mlp_output)
        time_logits = self.time_linear(mlp_output)

        if self.probabilistic:
            # Apply a probabilistic component to time prediction using reparameterization trick
            time_mean = time_logits
            time_log_var = torch.log(1 + torch.exp(time_logits))
            epsilon = torch.randn_like(time_log_var)
            time_logits = time_mean + epsilon * torch.exp(0.5 * time_log_var)

        return time_logits, event_logits

    def dispatch(self, tensors):
        for i in range(len(tensors)):
            tensors[i] = tensors[i].to(device).contiguous()
        return tensors

    def train_batch(self, batch):
        self.train()
        time_tensor, event_tensor = batch
        time_input, time_target = self.dispatch([time_tensor[:, :-1], time_tensor[:, -1]])
        event_input, event_target = self.dispatch([event_tensor[:, :-1], event_tensor[:, -1]])

        self.optimizer.zero_grad()
        time_logits, event_logits = self.forward(time_input, event_input)
        loss1 = self.time_criterion(time_logits.view(-1), time_target.view(-1))
        loss2 = self.event_criterion(event_logits.view(-1, self.n_class), event_target.view(-1))
        loss = self.config.alpha * loss1 + loss2
        loss.backward()

        self.optimizer.step()
        self.scheduler.step()
        return loss1.item(), loss2.item(), loss.item()

    def predict(self, batch):
        self.eval()
        time_tensor, event_tensor = batch
        time_input, time_target = self.dispatch([time_tensor[:, :-1], time_tensor[:, -1]])
        event_input, event_target = self.dispatch([event_tensor[:, :-1], event_tensor[:, -1]])
        with torch.no_grad():
            time_logits, event_logits = self.forward(time_input, event_input)
        event_pred = np.argmax(event_logits.detach().cpu().numpy(), axis=-1)
        time_pred = time_logits.detach().cpu().numpy()
        return time_pred, event_pred

# Configuration for Taxi Dataset
class Config:
    def __init__(self):
        self.event_class = 10
        self.emb_dim = 32
        self.hid_dim = 64
        self.mlp_dim = 64
        self.dropout = 0.2
        self.lr = 0.001
        self.alpha = 0.5
        self.model = 'deterministic'

config = Config()

# Instantiate deterministic and probabilistic models
```

```
deterministic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=False).to(device)
probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to(device)

# Call set_optimizer for both models
deterministic_model.set_optimizer(total_step=len(dataloader), use_bert=False) # This line was missing
probabilistic_model.set_optimizer(total_step=len(dataloader), use_bert=False)

# Load the dataset from HuggingFace
dataset = load_dataset('easytpp/taxi')

# Extract features from the train split using the correct column names
x_times_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.float32) for seq in dataset['train']['time_since_last_event']],
    batch_first=True,
    padding_value=0.0  # Choose an appropriate padding value
).to(device)
y_events_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.long) for seq in dataset['train']['type_event']],
    batch_first=True,
    padding_value=config.event_class - 1  # pad with the last event type index by default
).to(device)

# Create a TensorDataset and DataLoader with the loaded real dataset
train_dataset = TensorDataset(x_times_train_padded, y_events_train_padded)
dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)

# Training Loop for Deterministic Model
deterministic_losses = []
print("Training Deterministic Model")
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = deterministic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    deterministic_losses.append(avg_loss)
    print(f"Epoch [{epoch+1}/10], Loss: {avg_loss:.4f}")

# Training Loop for Probabilistic Model
probabilistic_losses = []
print("\nTraining Probabilistic Model")
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = probabilistic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    probabilistic_losses.append(avg_loss)
    print(f"Epoch [{epoch+1}/10], Loss: {avg_loss:.4f}")

# Example prediction for both models
with torch.no_grad():
    for batch in dataloader:
        print("\nDeterministic Model Predictions:")
        time_pred, event_pred = deterministic_model.predict(batch)
        print("Time Predictions:", time_pred)
        print("Event Predictions:", event_pred)

        print("\nProbabilistic Model Predictions:")
        time_pred, event_pred = probabilistic_model.predict(batch)
        print("Time Predictions:", time_pred)
        print("Event Predictions:", event_pred)
        break  # Only show predictions for the first batch

# Data Visualization
plt.figure(figsize=(12, 6))
plt.plot(range(1, 11), deterministic_losses, label='Deterministic Model Loss', marker='o')
plt.plot(range(1, 11), probabilistic_losses, label='Probabilistic Model Loss', marker='o')
plt.xlabel('Epoch')
plt.ylabel('Average Loss')
plt.title('Training Loss Comparison between Deterministic and Probabilistic Models')
plt.legend()
plt.grid(True)
plt.show()
```

```
Training Deterministic Model
Epoch [1/10], Loss: 1.0022
Epoch [2/10], Loss: 0.5369
Epoch [3/10], Loss: 0.5203
Epoch [4/10], Loss: 0.5196
Epoch [5/10], Loss: 0.5281
Epoch [6/10], Loss: 0.5235
Epoch [7/10], Loss: 0.5224
Epoch [8/10], Loss: 0.5201
Epoch [9/10], Loss: 0.5232
Epoch [10/10], Loss: 0.5243

Training Probabilistic Model
Epoch [1/10], Loss: 1.6400
Epoch [2/10], Loss: 1.1365
Epoch [3/10], Loss: 1.1349
Epoch [4/10], Loss: 1.1234
Epoch [5/10], Loss: 1.1313
Epoch [6/10], Loss: 1.1563
Epoch [7/10], Loss: 1.1293
Epoch [8/10], Loss: 1.1263
Epoch [9/10], Loss: 1.1268
```

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

```
Time Predictions: [[ 0.2406949 ]
 [ 0.24002378]
 [ 0.23682137]
 [-0.0062955 ]
```

Added in: Contrasting Deterministic and Probabilistic Models

```
from datasets import load_dataset
from torch.utils.data import DataLoader, TensorDataset
from torch.nn.utils.rnn import pad_sequence
import torch
from torch import nn
from torch.optim import Adam
from torch.optim.lr_scheduler import StepLR

# Load the Taxi dataset from Hugging Face
dataset = load_dataset('easytpp/taxi')

# Convert 'time_since_last_event' to tensors and pad sequences
x_times_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.float32) for seq in dataset['train']['time_since_last_event']],
    batch_first=True,
    padding_value=0.0  # Padding value for time differences
).to('cpu')  # Use 'cpu' or 'cuda' depending on your device

# Convert 'type_event' to tensors and pad sequences
y_events_train_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.long) for seq in dataset['train']['type_event']],
    batch_first=True,
    padding_value=9  # Assuming event_class = 10; use (event_class - 1) for padding
).to('cpu')  # Use 'cpu' or 'cuda' depending on your device


# Create a TensorDataset and DataLoader with the loaded real dataset
train_dataset = TensorDataset(x_times_train_padded, y_events_train_padded)
dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)

# Create a TensorDataset and DataLoader with the processed dataset
train_dataset = TensorDataset(x_times_train_padded, y_events_train_padded)
dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)

# Configuration for Taxi Dataset
class Config:
    def __init__(self):
        self.event_class = 10
        self.emb_dim = 32
        self.hid_dim = 64
        self.mlp_dim = 64
        self.dropout = 0.2
        self.lr = 0.001
        self.alpha = 0.5
        self.model = 'probabilistic'

# Negative Log-Likelihood Loss
def nll_loss(time_true, time_mean, time_logvar):
    loss = 0.5 * (time_logvar + ((time_true - time_mean) ** 2) / time_logvar.exp())
    return loss.mean()

# Define the PointProcessNet model
class PointProcessNet(nn.Module):
    def __init__(self, config, lossweight, probabilistic=False):
        super(PointProcessNet, self).__init__()
        self.config = config
        self.probabilistic = probabilistic
        self.n_class = config.event_class

        # Embedding for event types
        self.embedding = nn.Embedding(num_embeddings=config.event_class, embedding_dim=config.emb_dim)
        self.emb_drop = nn.Dropout(p=config.dropout)

        # LSTM for sequential modeling
        self.lstm = nn.LSTM(input_size=config.emb_dim + 1,
                            hidden_size=config.hid_dim,
                            batch_first=True,
                            bidirectional=False)

        # MLP for feature extraction
        self.mlp = nn.Linear(in_features=config.hid_dim, out_features=config.mlp_dim)
        self.mlp_drop = nn.Dropout(p=config.dropout)

        # Prediction layers
        self.event_linear = nn.Linear(in_features=config.mlp_dim, out_features=config.event_class)
        self.fc_time_mean = nn.Linear(in_features=config.mlp_dim, out_features=1)
        self.fc_time_logvar = nn.Linear(in_features=config.mlp_dim, out_features=1)

        self.set_criterion(lossweight)
```

```
    def set_optimizer(self, total_step):
        self.optimizer = Adam(params=self.parameters(), lr=self.config.lr)
        self.scheduler = StepLR(self.optimizer, step_size=100, gamma=0.1)

    def set_criterion(self, weight):
        self.event_criterion = nn.CrossEntropyLoss(weight=torch.FloatTensor(weight).to('cpu'))
        if self.probabilistic:
            self.time_criterion = nll_loss
        else:
            self.time_criterion = nn.MSELoss()

    def forward(self, input_time, input_events):
        event_embedding = self.embedding(input_events)
        event_embedding = self.emb_drop(event_embedding)
        lstm_input = torch.cat((event_embedding, input_time.unsqueeze(-1)), dim=-1)
        hidden_state, _ = self.lstm(lstm_input)

        mlp_output = torch.tanh(self.mlp(hidden_state[:, -1, :]))
        mlp_output = self.mlp_drop(mlp_output)

        time_mean = self.fc_time_mean(mlp_output)
        time_logvar = self.fc_time_logvar(mlp_output)
        event_logits = self.event_linear(mlp_output)

        return time_mean, time_logvar, event_logits

    def train_batch(self, batch):
        self.train()
        time_tensor, event_tensor = batch
        time_input, time_target = time_tensor[:, :-1], time_tensor[:, -1]
        event_input, event_target = event_tensor[:, :-1], event_tensor[:, -1]

        self.optimizer.zero_grad()
        time_mean, time_logvar, event_logits = self.forward(time_input, event_input)

        # Compute losses
        if self.probabilistic:
            # Probabilistic model uses NLL loss
            loss_time = self.time_criterion(time_target, time_mean.view(-1), time_logvar.view(-1))
        else:
            # Deterministic model uses MSE loss
            loss_time = self.time_criterion(time_mean.view(-1), time_target)

        # Event type loss (cross entropy)
        loss_event = self.event_criterion(event_logits.view(-1, self.n_class), event_target.view(-1))

        # Total loss
        loss = self.config.alpha * loss_time + loss_event

        # Backpropagation
        loss.backward()
        self.optimizer.step()
        self.scheduler.step()

        return loss_time.item(), loss_event.item(), loss.item()


# Instantiate and train the probabilistic model
config = Config()
probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to('cpu')
probabilistic_model.set_optimizer(total_step=len(dataloader))

# Training loop
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = probabilistic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    print(f"Epoch [{epoch+1}/5], Loss: {avg_loss:.4f}")
```

```
Epoch [1/5], Loss: 0.6631
Epoch [2/5], Loss: -0.0535
Epoch [3/5], Loss: -0.0669
Epoch [4/5], Loss: -0.0838
Epoch [5/5], Loss: -0.0751
Epoch [6/5], Loss: -0.0887
Epoch [7/5], Loss: -0.0686
Epoch [8/5], Loss: -0.0721
Epoch [9/5], Loss: -0.0906
Epoch [10/5], Loss: -0.0821
```

```
def evaluate(model, dataloader, probabilistic=False):
    model.eval()
    mae_time = 0  # 时间预测的 MAE
    correct_events = 0  # 正确预测的事件数
    total_samples = 0  # 样本总数

    with torch.no_grad():
        for batch in dataloader:
            time_tensor, event_tensor = batch
            time_input, time_target = time_tensor[:, :-1], time_tensor[:, -1]
            event_input, event_target = event_tensor[:, :-1], event_tensor[:, -1]

            # 模型前向传播
            if probabilistic:
                time_mean, _, event_logits = model(time_input, event_input)
            else:
                time_mean, _, event_logits = model(time_input, event_input)

            # 时间预测 MAE
            mae_time += torch.abs(time_mean.view(-1) - time_target).sum().item()

            # 事件类型分类准确率
            event_pred = event_logits.argmax(dim=-1)
```

```
            correct_events += (event_pred == event_target).sum().item()
            total_samples += time_target.size(0)

    mae_time /= total_samples
    accuracy_event = correct_events / total_samples
    return mae_time, accuracy_event


# 数据预处理：验证集
x_times_valid_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.float32) for seq in dataset['validation']['time_since_last_event']],
    batch_first=True,
    padding_value=0.0
).to('cpu')

y_events_valid_padded = pad_sequence(
    [torch.tensor(seq, dtype=torch.long) for seq in dataset['validation']['type_event']],
    batch_first=True,
    padding_value=9
).to('cpu')

# 创建验证数据集和数据加载器
valid_dataset = TensorDataset(x_times_valid_padded, y_events_valid_padded)
valid_dataloader = DataLoader(valid_dataset, batch_size=16, shuffle=False)

# 确定性模型
deterministic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=False).to('cpu')
deterministic_model.set_optimizer(total_step=len(dataloader))

# 训练确定性模型
deterministic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=False).to('cpu')
deterministic_model.set_optimizer(total_step=len(dataloader))
for epoch in range(10):
    for batch in dataloader:
        loss1, loss2, loss = deterministic_model.train_batch(batch)
    print(f"Deterministic model training completed.")

# 训练概率模型
probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to('cpu')
probabilistic_model.set_optimizer(total_step=len(dataloader))
for epoch in range(10):
    for batch in dataloader:
        loss1, loss2, loss = probabilistic_model.train_batch(batch)
    print(f"Probabilistic model training completed.")

# 验证确定性模型
det_mae, det_acc = evaluate(deterministic_model, valid_dataloader, probabilistic=False)
print(f"Deterministic Model - MAE: {det_mae:.4f}, Accuracy: {det_acc:.4f}")

# 概率模型
probabilistic_model = PointProcessNet(config=config, lossweight=[1.0]*config.event_class, probabilistic=True).to('cpu')
probabilistic_model.set_optimizer(total_step=len(dataloader))

# 概率模型训练
for epoch in range(10):
    total_loss = 0
    for batch in dataloader:
        loss1, loss2, loss = probabilistic_model.train_batch(batch)
        total_loss += loss
    avg_loss = total_loss / len(dataloader)
    print(f"[Probabilistic Model] Epoch [{epoch+1}/5], Loss: {avg_loss:.4f}")

# 验证概率模型
prob_mae, prob_acc = evaluate(probabilistic_model, valid_dataloader, probabilistic=True)
print(f"Probabilistic Model - MAE: {prob_mae:.4f}, Accuracy: {prob_acc:.4f}")

print("Final Comparison:")
print(f"Deterministic Model - MAE: {det_mae:.4f}, Accuracy: {det_acc:.4f}")
print(f"Probabilistic Model - MAE: {prob_mae:.4f}, Accuracy: {prob_acc:.4f}")


import matplotlib.pyplot as plt

# 数据准备
metrics = ['MAE', 'Accuracy']
det_results = [det_mae, det_acc]
prob_results = [prob_mae, prob_acc]

# 绘制柱状图
x = range(len(metrics))
plt.bar(x, det_results, width=0.4, label='Deterministic', color='blue')
plt.bar([p + 0.4 for p in x], prob_results, width=0.4, label='Probabilistic', color='orange')

# 添加标签
plt.xticks([p + 0.2 for p in x], metrics)
plt.ylabel('Performance')
plt.title('Comparison of Deterministic and Probabilistic Models')
plt.legend()
plt.show()
```