Work Smarter, Not Harder: Towards An Efficient and Effective En Route Travel Time Estimation Framework

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ABSTRACT

En route travel time estimation (ER-TTE) focuses on predicting the travel time of the remaining route. Existing ER-TTE methods always make re-estimation which significantly hinders real-time performance, especially when faced with the computational demands of simultaneous user requests. This results in delays and reduced responsiveness in ER-TTE services. We propose a general efficient framework combining an Uncertainty-Guided Decision mechanism (UGD) and Fine-Tuning with Meta-Learning (FTML) to address these challenges. UGD quantifies the uncertainty and provides confidence intervals for the entire route. It selectively re-estimates only when the actual travel time deviates from the predicted confidence intervals, thereby optimizing the efficiency of ER-TTE. To ensure the accuracy of confidence intervals and accurate predictions that need to re-estimate, FTML is employed to train the model, enabling it to learn general driving patterns and specific features to adapt to specific tasks. Extensive experiments on two large-scale real datasets show that our framework can enhance inference speed by 2 to 6 times and increase throughput by 2 to 5 times while maintaining high effectiveness, demonstrating our framework's efficiency and effectiveness.

CCS CONCEPTS

• **Applied computing** → **Forecasting**; • **Spatialtemporal systems**;

KEYWORDS

Travel time estimation, Uncertainty quantification, Efficiency

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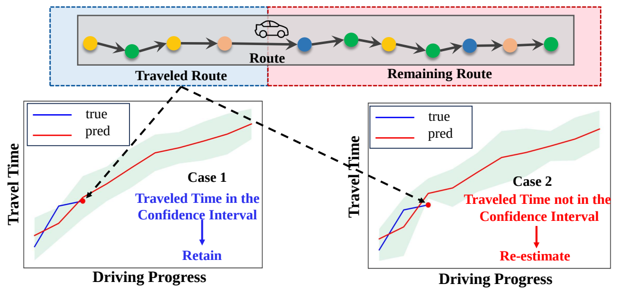


Figure 1: Uncertainty quantification in ER-TTE according to confidence intervals to decide whether to re-estimate.

1 INTRODUCTION

Travel Time Estimation (TTE) serves as a cornerstone of Intelligent Transportation Systems (ITS)[26], enabling the prediction of travel time for specific routes with departure time. This capability is crucial for a host of ITS applications, such as route planning [30], navigation [29], traffic forecasting [10, 25], and online ride-hailing services [15]. Most TTE methods are referred to as pre-route travel time estimation (PR-TTE) due to their focus on predicting the whole travel time before departure [23]. However, numerous practical TTE requirements are en route travel time estimations (ER-TTE), necessitating the real-time TTE process when driving. Although some studies [5, 6] have developed models for effective ER-TTE by integrating information on traveled routes and dynamic features, they often fail to simultaneously account for the model efficiency in real-time settings, which significantly impede the practical application of these models. To bridge this gap, the development of an efficient and effective ER-TTE framework faces the following challenges.

C1: *How to reduce the number of invoking estimation models without losing accuracy?* To provide timely navigation updates, ER-TTE must refresh remaining travel time estimates during the route. However, frequent model invocations cause delays due to inference time, and high concurrent user requests further strain system capacity. For instance, Didi reported an average of 33.01 million daily orders in China in Q3 2024 [1], illustrating the demand for simultaneous ER-TTE updates. Limited server processing power may lead to delays for some users. Therefore, minimizing unnecessary model calls while maintaining accuracy is essential to improving efficiency and throughput.

C2: How to ensure the robustness of the TTE model throughout the route? It's essential to balance general driving patterns with route-specific conditions. The model should learn common travel patterns across routes while quickly adapting to individual driving styles, such as unique acceleration or braking habits. Additionally, it must promptly adjust to unexpected conditions like traffic congestion or accidents to deliver accurate, real-time predictions. However, existing approaches [5, 6] mainly emphasize capturing user driving preferences. Although useful, these models often lack the flexibility to adapt to dynamically changing traffic situations based on real-time information.

In this paper, we introduce an efficient and effective framework to tackle the key challenges in ER-TTE, featuring an innovative Uncertainty-Guided Decision (UGD) mechanism and Fine-Tuning with Meta-Learning (FTML). The UGD mechanism optimizes request handling by strategically reusing previous estimates, thus minimizing redundant computations. As shown in Figure 4, the system first quantifies uncertainty across the entire route and stores confidence intervals. During travel, it monitors actual travel time. If travel time remains within the confidence intervals, the estimate is retained, avoiding unnecessary re-estimations. The ER-TTE is then derived by subtracting elapsed time from the initial estimate. Only when significant deviations occur, indicating changed traffic conditions, does the system trigger re-estimation. This UGD mechanism reduces model invocation frequency, addressing the challenge of high request volumes (i.e., **addressing C1**). Additionally, FTML is introduced to enhance prediction accuracy, using MAML [8] to pre-train on general driving patterns and then fine-tune for specific tasks, allowing rapid adaptation to route dynamics while preserving generalizability (i.e., **addressing C2**). Therefore, UGD and FTML significantly boost both the effectiveness and efficiency of ER-TTE.

In summary, the contributions can be summarized as follows:

(1) To our best knowledge, this study is the first to consider the efficiency of ER-TTE and achieve an efficient and effective ER-TTE framework.
(2) We propose an Uncertainty-Guided Decision mechanism (UGD) that determines adaptively whether ER-TTE needs to be re-estimated, offering a novel approach that can be integrated with existing TTE backbone models.
(3) We develop a new training strategy called Fine-Tuning with Meta-Learning (FTML) that enhances both generalizability and adaptability.
(4) Experiments on two large-scale real-world datasets verify the efficiency and effectiveness of the framework. Our approach significantly improves inference speed and throughput while maintaining high performance.

2 RELATED WORK

2.1 Travel Time Estimation

Travel time estimation can be classified the two types Origin-Destination based TTE (OD-TTE) and route-based TTE. OD-TTE refers to estimating travel time by providing only the origin, destination, and departure [15, 16, 18, 19, 22, 28],. In contrast, Route-based TTE requires additionally specific route information. Early route-based research utilizes regression or decomposition methods [11], achieving limited accuracy due to their constrained modeling capabilities. Recent advances have brought significant improvements: WDR [23] and its variant [17] employ wide-deep-recurrent networks for comprehensive route analysis; ConSTGAT [7] utilizes a graph attention network to extract the joint relationship of spatiotemporal information. [4] Using the graph neural network for TTE on Google Maps significantly improves effectiveness. DeepGTT [14] employs a variational encoder to capture the travel time distributions of trajectories to enhance prediction accuracy. HierETA [3] leverages Transformer and uses multi-view modeling. STHR [27] considers key characteristics in travel routes and combines the advantages of graph attention networks and Transformers. In the specific domain of ER-TTE, SSML [6] pioneered the meta-learning application, extracting meta-knowledge from traveled routes to predict remaining travel times. MetaER-TTE [5] advanced this approach with cluster-aware initialization and adaptive learning rate optimization. However, these methods focus on specific locations, rather than continuous route progression, which leads to efficiency issues and practical limitations in ER-TTE applications.

2.2 Uncertainty Quantification

Uncertainty quantification methods, widely applied to real-world problems, fall into two categories: Bayesian and non-Bayesian approaches [2]. Bayesian methods face the difficulty of directly calculating the posterior distribution, necessitating the use of approximate methods such as variational inference and Markov chain Monte Carlo (MCMC). Bayesian neural networks (BNNs) [21] utilize approximate Bayesian inference to enhance the efficiency of their inferential processes. Monte Carlo dropout (MC Dropout) [9] assumes that the parameters of each layer of the neural network follow a Bernoulli distribution, thereby controlling the drop probability of hidden layer neurons. Non-Bayesian methods, typically frequentist in nature, offer greater flexibility through techniques like quantile regression [12] and MIS regression [24], which embed uncertainty directly into loss functions.

3 PRELIMINARY

We first present the definition of the ER-TTE problem. Then, we describe how meta-learning is applied to ER-TTE and propose a pipeline with the Uncertainty-Guided Decision mechanism to achieve efficient and effective ER-TTE.

3.1 En Route Travel Time Estimation

Given a driving route $R = [s_1, s_2, \ldots, s_n]$ composed of n road segments, and considering current segment s_m $(1 \leq m < n)$ at time t, the route can be segmented into two parts: traveled route $R_{tr} = [s_1, s_2, \ldots, s_m]$ and remaining route $R_{re} = [s_{m+1}, s_{m+2}, \ldots, s_n]$. Specifically, the travel time for the traveled portion of route R_{tr} is known and denoted as y_{tr}. The objective of the en route travel time estimation (ER-TTE) task is to predict the travel time for the remaining portion of route R_{re}. This task can be formally described by function:

$$\hat{y}_{re} = f_\theta(t, y_{tr}, R_{tr}, R_{re}),$$

where f_θ denotes the ER-TTE model, θ represents the model parameters, t is the current time, and $\hat{y}_{re}$ is the estimated travel time for R_{re}.

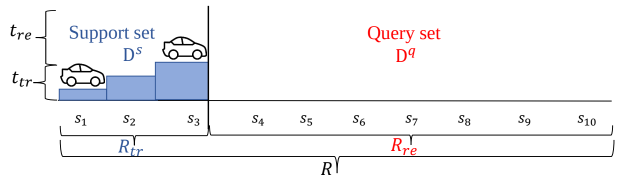
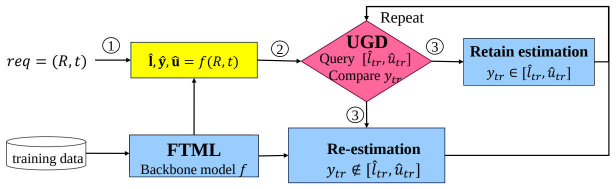


Figure 2: An explanation of Meta-Learning for ER-TTE



$req = (R, t)$
①
$\hat{\mathbf{l}}, \hat{\mathbf{y}}, \hat{\mathbf{u}} = f(R, t)$
②
UGD
Query $[\hat{l}_{tr}, \hat{u}_{tr}]$
Compare y_{tr}
Repeat
③
Retain estimation
$y_{tr} \in [\hat{l}_{tr}, \hat{u}_{tr}]$
③
training data
FTML
Backbone model f
Re-estimation
$y_{tr} \notin [\hat{l}_{tr}, \hat{u}_{tr}]$

Figure 3: Overview of our ER-TTE framework.

3.2 Meta-Learning in ER-TTE

Meta-learning, commonly called "learning to learn", is designed to train models capable of rapidly adapting to new tasks with limited new data. This approach enables a meta-learner to guide the model in effectively learning from diverse tasks. In the context of the ER-TTE problem, meta-learning is employed to discern general patterns of the entire routes, allowing the model to tailor its predictions to the specific nuances of ER-TTE scenarios. Such as the traveled routes contain driver preferences such as acceleration.

In the meta-learning framework applied to ER-TTE, the dataset is strategically split into a support set and a query set. Following the setting of prior research [5, 6], the traveled portion of the route R_{tr} is utilized as the support set D^s, while the untraveled segment R_{re} is treated as the query set D^q. This division aids the model in leveraging past experiences (support set) to make informed predictions about future segments (query set) of the route. A graphical representation of the support and query sets for a specific route is illustrated in Figure 2. This methodological approach underscores the adaptability and foresight that meta-learning imparts to the ER-TTE model.

4 METHODOLOGY

In this section, we first outline the complete framework in Sec. 4.1. Specifically, two key modules (i.e., UGD and FTML) are discussed in greater detail in Sec. 4.2 and Sec. 4.3, respectively.

4.1 Overview

To enhance the efficiency and accuracy of the ER-TTE process, we propose a simple yet effective framework as depicted in Figure 3. At first, for a given request $req = (R, t)$, the model f first estimates the travel time $\hat{\mathbf{y}}$ and the associated confidence intervals for the entire route before departure, utilizing the Fine-Tuning with Meta-Learning (FTML) strategy. The initial confidence intervals, denoted as $\hat{\mathbf{l}}$ and $\hat{\mathbf{u}}$, encapsulates the predicted travel time from the origin to the destination. Subsequently, during the route, the Uncertainty-Guided Decision (UGD) mechanism is employed to continuously assess the alignment between the actual travel time and the estimated confidence intervals. If the actual travel time y_{tr} falls within the current confidence interval $[\hat{l}_{tr}, \hat{u}_{tr}]$, the existing estimation is retained. Conversely, if y_{tr} deviates from $[\hat{l}_{tr}, \hat{u}_{tr}]$, a re-estimation is triggered using model f, and this validation cycle is repeated throughout the route to ensure reliable predictions.

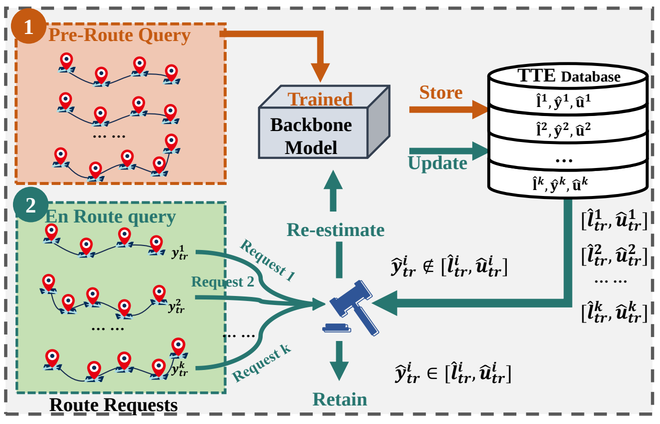
Remark. We divide the entire route for k parts. The terms $\hat{\mathbf{l}} = \{l_1, l_2, ..., l_k\}$ and $\hat{\mathbf{u}} = \{u_1, u_2, ..., u_k\}$ represent the lower and upper bounds of the confidence intervals of the entire route, representing the complete range of expected travel times from origin to destination. In contrast, $[\hat{l}, \hat{u}]$ specifies the confidence interval at a particular point along the route.

4.2 Uncertainty-Guided Decision Mechanism

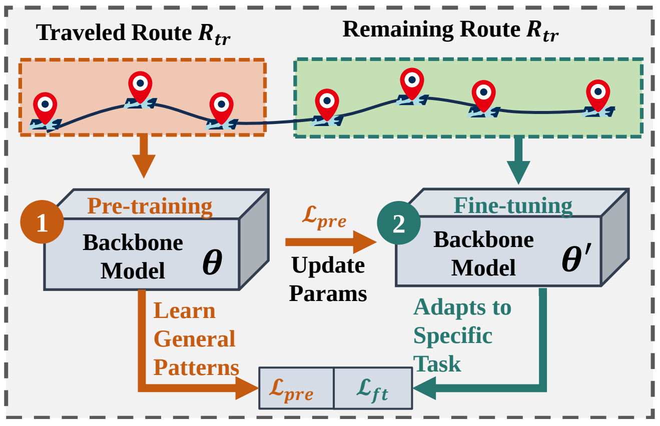
Motivation. To improve the efficiency of ER-TTE and minimize system resource consumption under the large request frequency, it is intuitive to design a decision mechanism to determine whether a re-estimation is needed at the request time t during the driving. Travel time is influenced by unpredictable factors, such as traffic congestion and road accidents, which introduce uncertainty into the predictions. Therefore, quantifying uncertainty allows us to capture the variability in TTE. Accordingly, we propose an Uncertainty-Guided Decision (UGD) Mechanism, quantifying the uncertainty in the route to make decisions.

Overview. As illustrated in Figure 4b, the Uncertainty-Guided Decision (UGD) process is categorized into two distinct phases: *pre-route query* and *en route query*. Initially, in the pre-route query phase, the trained backbone model is utilized to compute the confidence intervals for each route prior to departure, which are then stored in the TTE database. Subsequently, in the en route query phase, these confidence intervals are employed to verify the accuracy of ongoing predictions. If the actual travel time deviates from the established confidence intervals, indicating the necessity for adjustments, the model is invoked to re-estimate the travel time for the remainder of the route, updating the corresponding confidence intervals in the TTE database accordingly. If the current predictions fall within the confidence intervals, the existing estimations are retained to respond to the en route queries. Notably, the key point is to calculate, store, and update confidence intervals due to that the confidence intervals provide a solid foundation for decision-making.

Decision-Making Algorithm. The entire procedure employing the Uncertainty-Guided Decision (UGD) mechanism is outlined in Algorithm 1. Initially, we utilize the model to generate preliminary predictions for the pre-route query, represented as $\hat{\mathbf{y}}$, along with the associated confidence intervals for the entire route, denoted as $\hat{\mathbf{l}}$ (lower bounds) and $\hat{\mathbf{u}}$ (upper bounds) (lines 1-3). These predictions and confidence intervals are subsequently stored in a database, laying the groundwork for the en route query stage. There are k parts in the route which system queries at specific locations. For each part i,the system compares the actual travel time y^i_{tr} with confidence interval $[\hat{l}^i_{tr}, \hat{u}^i_{tr}]$. If the actual travel time resides within the confidence interval, i.e., $y^i_{tr} \in [\hat{l}^i_{tr}, \hat{u}^i_{tr}]$, the prediction is considered accurate, and the original estimate is retained. The ER-TTE is calculated by subtracting the prediction for the traveled route from the initial estimate (lines 7-9). Conversely, if the actual travel time falls outside the confidence interval i.e., $y^i_{tr} \notin [\hat{l}^i_{tr}, \hat{u}^i_{tr}]$, this discrepancy suggests significant uncertainty and possible inaccuracies in the



(a) Fine-Tuning with Meta-Learning.


Traveled Route R_{tr}
Remaining Route R_{tr}
1 Pre-training Backbone Model θ
$\mathcal{L}_{pre}$ Update Params
2 Fine-tuning Backbone Model θ'
Learn General Patterns
Adapts to Specific Task
$\mathcal{L}_{pre}$ $\mathcal{L}_{ft}$

(b) Uncertainty-Guided Decision.

Figure 4: Overall Framework

Algorithm 1 Uncertainty-Guided Decision.

```
Require: Entire route $R$; traveled routes $\{R^1_{tr}, R^2_{tr}, ..., R^k_{tr}\}$;
    Remained routes $\{R^1_{re}, R^2_{re}, ..., R^k_{re}\}$; trained model $f_\theta$;

1: // Pre-route query
2: $\hat{\mathbf{l}}, \hat{\mathbf{y}}, \hat{\mathbf{u}} = f_\theta(R, t)$;
3: UGD.store(confidence intervals);
4: // En route query during the route
5: for $i \longleftarrow 1...k$ do:
6:     UGD.query($y^i_{tr}, R^i_{tr}$) ;
7:     if $y^i_{tr} \in [\hat{l}^i_{tr}, \hat{u}^i_{tr}]$:
8:     // actual traveled time $y^i_{tr}$ falls within confidence interval
9:         $[\hat{l}^i_{re}, \hat{y}^i_{re}, \hat{u}^i_{re}] = [l - \hat{l}^i_{tr}, \hat{y} - \hat{y}^i_{tr}, u - \hat{u}^i_{tr}]$;
10:    else: // re-estimation
11:        $[\hat{l}^i_{re}, \hat{y}^i_{re}, \hat{u}^i_{re}] = f_\theta(t, y^i_{tr}, R^i_{tr}, R^i_{re})$;
12:        UGD.update(confidence intervals)
13:    end for
```

prediction, necessitating a re-estimation. In such cases, the system recalculates the travel time using updated route information. (lines 10-12).

Formally, the application of UGD in the en route query can be represented by the following equation:

$$\text{UGD}\left(t, y_{tr}, R_{tr}, R_{re}, [\hat{l}_{tr}, \hat{u}_{tr}]\right) = \begin{cases} \hat{y} - \hat{y}_{tr} & \text{if } y_{tr} \in [\hat{l}_{tr}, \hat{u}_{tr}], \\ f(t, R_{tr}, R_{re}) & \text{if } y_{tr} \notin [\hat{l}_{tr}, \hat{u}_{tr}]. \end{cases} \tag{1}$$

Efficiency Analysis. The backbone model complexity is $O(m)$, where m depends on the components of model and input dimensions. When the UGD decides to retain estimation, the need for re-invoking the backbone model is bypassed, thereby reducing the complexity to $O(1)$. Specifically, assuming a confidence level of p (e.g., $p = 0.8$), indicating that there is an 80% probability that no re-estimation will be needed for a given request during the route, the process predominantly operates at $O(1)$ complexity. As the confidence level increases, the proportion of requests that do not require re-estimation grows, leading to a further reduction in overall time complexity. Consequently, The computational overhead is significantly reduced.

Algorithm 2 Fine-Tuning with Meta-Learning.

```
Require: Entire route $R$; traveled route $R_{tr}$; model parameters $\theta$;
total epoch N; total iteration $n_{\text{iter}}$.
1: for i ← 1 to N:
2:     while $n < n_{\text{iter}}$:
3:         // pre-train
4:         $\hat{l}, \hat{y}, \hat{u} = f_\theta(R)$;    $\hat{l}_{tr}, \hat{y}_{tr}, \hat{u}_{tr} = f_\theta(R_{tr})$.
5:         compute the loss function according to Equation (8);
6:         Update $\theta' \leftarrow \theta - lr \cdot \nabla_\theta \mathcal{L}_{pre}(\theta)$;
7:         // fine-tune
8:         $\hat{l}_{re}, \hat{y}_{re}, \hat{u}_{re} = f_{\theta'}(R_{re}, R_{tr})$;
9:         compute the loss function according to Equation (12);
10:        Update $\theta \leftarrow \theta - lr \cdot \nabla_\theta(\mathcal{L}_{re}(\theta') + \mathcal{L}_{pre}(\theta))$;
11:    end while
12: Return $\theta$
```

4.3 Fine-Tuning with Meta-learning

Motivation. To ensure the robustness of TTE models throughout the entire route, on the one hand, the model must effectively learn and generalize driving patterns across various routes to provide a solid foundation for understanding stable driving preferences. On the other hand, the model must be flexible enough to adapt to dynamically changing traffic scenarios, allowing it to adjust predictions based on real-time data. With these goals in mind, we implement Fine-Tuning with Meta-Learning (FTML) to enhance both generalizability and adaptability. **Overview.** As shown in Figure 4a, FTML consists of two different stages: *pre-training* and *fine-tuning*. In the pre-training stage, the model is trained to predict both the total route arrival time $\hat{y}$ and the traveled time $\hat{y}_{tr}$ at specific locations, along with their respective confidence intervals.

The model parameters are updated to enable the model to learn general driving patterns. In the fine-tuning stage, the model is further trained to predict the travel time $\hat{y}_{re}$ and the confidence interval for the remaining route. This allows the model to adjust predictions based on real-time data, enhancing its ability to adapt to changing conditions during the route.

Learning Algorithm. The FTML procedure is depicted in Algorithm 2. In pre-training stage, the model is initialized with effective weights to learn general driving patterns for the entire route and specific features of the traveled route. The focus is on training the model to estimate the travel time $\hat{y}$ and its confidence interval $[\hat{l}, \hat{u}]$ for the entire route R as well as the traveled time $\hat{y}_{tr}$ and its confidence interval $[\hat{l}_{tr}, \hat{u}_{tr}]$ for traveled route R_{tr} within the support set D^s.

$$\hat{l}, \hat{y}, \hat{u} = f_\theta(R), \tag{2}$$

$$\hat{l}_{tr}, \hat{y}_{tr}, \hat{u}_{tr} = f_\theta(R_{tr}). \tag{3}$$

To accurately supervise the predictions and corresponding confidence intervals, we employ *quantile regression* [12], which is a robust and effective method for quantifying uncertainty. Quantile regression is distribution-free and directly optimizes the quantile loss function for providing precise supervision on specific quantile values without requiring any external parameters. In particular, its basic form is illustrated as follows:

$$\begin{aligned}\mathcal{L}^{qua} =& \mathbb{I}_{\hat{l}\geq y}\alpha^{\hat{l}}\left|y-\hat{l}\right| + \mathbb{I}_{\hat{l}<y}\left(1-\alpha^{\hat{l}}\right)\left|y-\hat{l}\right| + \\ & \mathbb{I}_{\hat{y}\geq y}\alpha^{\hat{y}}\left|y-\hat{y}\right| + \mathbb{I}_{\hat{y}<y}\left(1-\alpha^{\hat{y}}\right)\left|y-\hat{y}\right| + \\ & \mathbb{I}_{\hat{u}\geq y}\alpha^{\hat{u}}\left|y-\hat{l}\right| + \mathbb{I}_{\hat{u}<y}\left(1-\alpha^{\hat{u}}\right)\left|y-\hat{l}\right|,\end{aligned} \tag{4}$$

where α is the quantile $(0 < \alpha < 1)$, $\mathbb{I}$ is the indicator function. This loss function is to evaluate the relationship between $\hat{l}, \hat{y}, \hat{u}$ and the label y, applying different weights based on the target quantile α. Specifically, the $\alpha^{\hat{l}} < 0.5$, the loss function imposes a greater penalty for cases where the prediction is lower than the label (i.e., lower bound). Conversely, when $\alpha^{\hat{u}} > 0.5$, the loss function imposes a greater penalty for cases where the prediction is higher than the label (i.e., upper bound). $\alpha^{\hat{y}} = 0.5$, the loss function is for the predication $\hat{y}$.

Building on this, we define a composite loss L_{pre} for the pre-training stage that integrates the quantile loss $\mathcal{L}_{en}$ for the entire route R and the quantile loss $\mathcal{L}_{tr}$ in support set D^s. To further refine the confidence interval, we use Mean Prediction Interval Width (MPIW) [20] to constrain the confidence interval to ensure it remains tight and reliable throughout the route.

$$\mathcal{L}_{en}(\theta) = \mathcal{L}^{qua}([\hat{l}, \hat{y}, \hat{u}], y), \tag{5}$$

$$\text{MPIW} = \hat{u}_{tr} - \hat{l}_{tr}, \tag{6}$$

$$\mathcal{L}_{tr}(\theta) = \mathcal{L}^{qua}([\hat{l}_{tr}, \hat{y}_{tr}, \hat{u}_{tr}], y_{tr}) + \text{MPIW}. \tag{7}$$

The total loss $\mathcal{L}_{pre}$ of the pre-training stage is given by the sum of the two losses (lines 4-5):

$$\mathcal{L}_{pre}(\theta) = \mathcal{L}_{en}(\theta) + \mathcal{L}_{tr}(\theta). \tag{8}$$

Then update the model parameters θ through the $\mathcal{L}_{pre}$ (line 6):

$$\theta' \leftarrow \theta - lr \cdot \nabla_\theta \mathcal{L}_{pre}(\theta), \tag{9}$$

where lr is the learning rate and θ' denotes the updated model parameters. By the end of this stage, the model achieves a good weight initialization, enabling it to rapidly adapt to new tasks (i.e.,ER-TTE) in the fine-tuning stage and make accurate predictions.

During the fine-tuning stage, the inputs for this stage include features of both the already traveled and remaining routes which ensure that the model can adapt to the dynamic traffic conditions of partially traveled routes and then provide accurate ER-TTE. The pre-trained model with parameters θ' is fine-tuned specifically for prediction $\hat{y}_{re}$ and its confidence interval $[\hat{l}_{re}, \hat{u}_{re}]$ for the remaining route in the query set D^q. The fine-tuning quantile loss $\mathcal{L}_{ft}$ for the remaining route is calculated as follows (lines 8-9):

$$\hat{l}_{re}, \hat{y}_{re}, \hat{u}_{re} = f_{\theta'}(R_{re}, R_{tr}), \tag{10}$$

$$\mathcal{L}_{ft}(\theta') = \mathcal{L}^{qua}([\hat{l}_{re}, \hat{y}_{re}, \hat{u}_{re}], y_{re}). \tag{11}$$

The model parameters are finally updated based on the two losses (line 10).

$$\theta \leftarrow \theta - lr \cdot \nabla_\theta(\mathcal{L}_{ft}(\theta') + \mathcal{L}_{pre}(\theta)). \tag{12}$$

In summary, FTML makes the model generalize from previous tasks (entire and traveled TTE) and swiftly adapt to new tasks (ER-TTE) through a two-stage training process: *pre-training* and *fine-tuning*. During *pre-training*, the model captures general driving patterns for entire routes and the specific features from the traveled route, enabling it to understand the overall dynamics of travel time across different routes. The *fine-tuning* stage allows the model to specialize in the task of ER-TTE, ensuring that it can adapt to the specific conditions of partially traveled routes and provide accurate predictions.

5 EXPERIMENT

In this section, we present the performance of our framework. We evaluate its effectiveness, efficiency, and scalability by applying several advanced TTE models and conducting ablation studies. Additionally, we perform online tests using simulated streaming data to validate our framework further.

5.1 Experimental Settings

Datasets and Preprocessing. We utilize two real-world taxi trajectory datasets collected from the cities of Porto[1], and Xian[2]. For both datasets, We removed outlier data (i.e. driving distances that were too short and too long). The processed Porto dataset contains 1,011,761 routes and Xian contains 1,191,125 routes **Metrics**. Similar to existing methods [3, 13], we use four metrics for performance evaluation, including mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), and satisfaction rate (SR). Specifically, SR refers to the proportion of routes with a MAPE less than 10%, and a higher SR indicates better performance and customer satisfaction. They are defined as follows: $\text{SR} = \frac{1}{N}\sum_i^N(|\frac{\hat{y}_i - y}{y}| \leq 10\%) \times 100\%$

Implementation Details. The Adam optimizer is used with a fixed learning rate of 1×10^-3 and a weight decay of 1×10^-3 as a regularization term to prevent overfitting. We use the training set to train the model, select the model with the best MAPE on the

[1]https://www.kaggle.com/c/pkdd-15-predict-taxi-service-trajectory-i
[2]https://gaia.didichuxing.com/

validation set, and use the test set to evaluate the performance. All experiments are implemented in Python using the Pytorch toolbox, using an NVIDIA RTX A4000 GPU. The platform runs on an Ubuntu 20.04 operating system. Following [5], each route is divided into two parts: **30%** of the route has already been traveled and **70%** remaining route. The quantities α are [0.1,0.5,0.9].

We compare two strategies that can improve throughput: (1)**Random**: All samples are not specially processed and are first come, first served. (2)**Greedy**: Since long routes are often difficult to predict, long-distance routes are predicted first. We re-estimate samples that could not be effectively filtered under various strategies. For samples that are successfully filtered, the prediction value is calculated as $\hat{y} - y_{tr}$.

Backbone Architectures We select two groups of backbones including different architecture and integrate them into our framework. As shown in Table 2, we analyze the time complexity of different backbone models.

1. TTE Method: (1)**MLPTTE**: A 16-layer multilayer perceptron with ReLU activation function is used. The specific approach is to estimate the travel time of each road segment separately and sum it as the overall travel time estimate of the route. (2)**WDR** [23]: a wide-deep-recurrent architecture is introduced to handle sparse features, dense features, and road segment sequence features respectively. (3)**WDR-LC** [17]:Enhances WDR by jointly modeling road segments and intersections. (4)**ConSTGAT** [7]: It is a spatiotemporal graph neural network structure that uses graph attention to capture spatiotemporal correlations and the contextual information of the route.

2. ER-TTE Method: (5)**SSML** [6]: It is the first meta-learning model for ER-TTE, which aims to learn meta-knowledge to quickly adapt to users' driving preferences. (6)**MetaER-TTE** [5]: A new adaptive meta-learning model is proposed, which generates cluster-aware initialization parameters through soft clustering and uses distribution-aware adaptive learning rate optimization.

5.2 Overall Effectiveness Comparison

As shown in Table 1, We analyze the effectiveness in two aspects, e.g., Overall comparison and Model fitness.

Overall Comparison. We using different backbone models with UGD improves average MAPE, MAE, RMSE and SR by at least 24.3%, 17.6%, 12.6%, and 18% in on Porto dataset, and 16.7%, 10.3%, 7.5%, and 8.9% on Xian dataset. This demonstrates the effectiveness of UGD in identifying routes needing re-estimation, and achieving SOTA results. In contrast, the greedy strategy performs worse due to higher prediction errors on longer routes.

Model Fitness. The attention-based models ConSTGAT, MetaER-TTE, and SSML perform well Because the attention mechanism can integrate information from different segments to obtain accurate predictions. The MLP-based MLPTTE model uses a pure MLP architecture to independently process the features of each road segment and sum them as an estimated value. Although it ignores the association between road segments, it shows advantages in processing independent and complex road segment features.

The RNN-based models WDR and WDR-LC have a slightly poorer performance, which may be because each step of the RNN is calculated based only on the current input and the hidden state of the previous time step. Although RNN can partially integrate historical information, its processing method may not effectively capture the complex associations between different locations, especially when it is necessary to capture the state of the intermediate process of the vehicle's driving process. This causes the RNN-based model to inaccurately estimate travel time, making it difficult to construct an effective confidence interval.

5.3 Efficiency Comparison

We analyze the efficiency in inference time and throughput(the number of samples that can be processed per second). As shown in Figure 5, w/o UGD means without UGD which all samples re-estimate. On the Xian dataset, MLPTTE, WDR, WDR-LC, ConST-GAT, and SSML do not require model calls in 77.3%, 32.1%, 24.7%, 77.5%, and 78.1% of cases, respectively. On the Porto dataset, these models perform 80.3%, 74.2%, 37.9%, 36.7%, 73.9%, and 70.7%, respectively. We have the following observations:

(1) The experimental results demonstrate that integrating UGD inference time and throughput by at least 1.49 times and 2.97 times, respectively, on the Porto dataset, and by 1.2 times and 2.67 times on the Xian dataset.

(2) Three Attention-based models and MLPTTE can filter more samples and make greater progress. More routes need re-estimation with two RNN-based methods, resulting in smaller improvements. However, they improved by 1.2 and 2.67 times in inference time and throughput, respectively.

The improvements are attributed to the ability of UGD to minimize unnecessary inference operations, optimize the use of computational resources, and accelerate system response time.

5.4 Scalability Comparison

To validate the scalability of our framework, we use 20%, 40%, 60%, and 80% of the training data and conduct detailed experimental analysis. As shown in Figure 6, we observe the following:

(1) The performance of all methods improves with increased training data. This is because a larger dataset encompasses a wider range of scenarios, enabling the model to learn more effectively.

(2) Attention-based models are more stable and effective than RNN-based models. Attention-based models can get good performance using only 20% training data. However, RNN-based models can only be greatly improved as data increases.

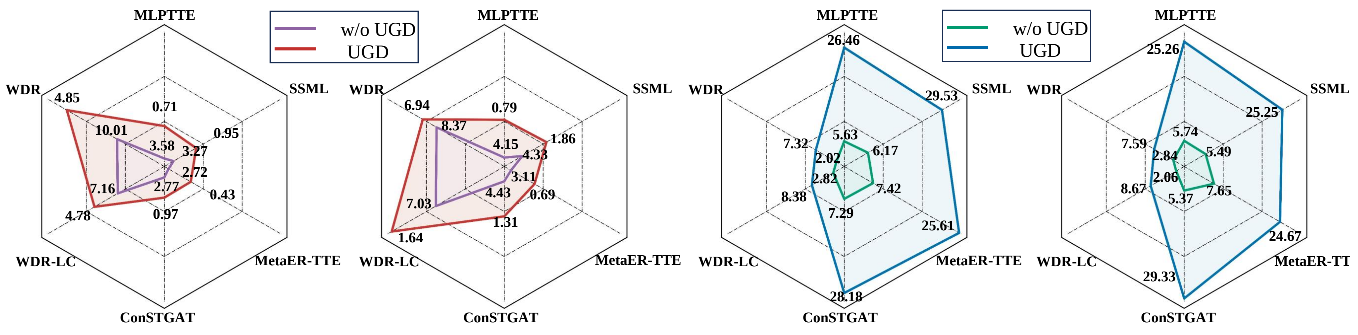
5.5 Ablation Study

To validate the effectiveness of our method, we design ablation studys, which includes the following two parts: (1) w/o FTML: Removing the FTML, (2) MIS: Replacing quantile loss to MIS (Mean Interval Score) loss [24]. As shown in Table 3, we do the ablation study on SSML.

First, performance decreases without FTML, indicating FTML makes the model learn the general patterns and specific features to adapt to specific tasks. Additionally, the MIS method shows a significant decrease in both effectiveness and uncertainty quantification. This proves quantile loss not only provides accurate confidence intervals to enhance efficiency but also improves the overall prediction effectiveness.

Table 1: Overall performance on Porto and Xian dataset

Method	strategy	Porto				Xian			
		MAPE (%)↓	MAE (s)↓	RMSE (s)↓	SR (%)↑	MAPE (%)↓	MAE (s)↓	RMSE (s)↓	SR (%)↑
MLPTTE	Random	22.25	116.45	255.04	38.53	23.75	200.75	312.71	29.90
	Greedy	23.90	122.03	258.30	36.35	28.81	217.87	309.41	25.98
	UGD	**16.09**	**91.04**	**214.19**	**47.19**	**18.85**	**170.83**	**275.37**	**35.36**
WDR	Random	46.667	343.86	493.88	10.61	29.78	347.44	492.96	18.56
	Greedy	40.22	240.24	359.06	20.86	36.13	370.64	475.88	16.21
	UGD	**20.08**	**111.28**	**236.03**	**36.71**	**20.63**	**193.95**	**327.10**	**32.01**
WDR-LC	Random	32.69	234.09	384.21	24.34	32.72	381.16	530.64	16.18
	Greedy	44.15	287.5	417.41	14.11	36.66	363.42	476.42	19.43
	UGD	**19.23**	**111.27**	**243.54**	**40.54**	**21.88**	**190.82**	**294.56**	**30.34**
ConSTGAT	Random	23.24	121.40	257.38	37.24	25.024	209.19	319.02	28.52
	Greedy	26.84	129.93	252.64	27.08	25.72	215.85	323.57	26.98
	UGD	**15.86**	**91.76**	**217.85**	**48.75**	**20.83**	**176.09**	**269.62**	**32.82**
SSML	Random	22.92	116.21	248.36	36.54	24.39	211.95	332.44	29.26
	Greedy	32.39	134.37	241.69	25.17	25.77	211.56	315.78	27.68
	UGD	**16.89**	**90.15**	**210.03**	**46.30**	**19.14**	**170.10**	**272.28**	**35.40**
MetaER-TTE	Random	25.41	129.86	264.13	31.64	24.20	200.94	304.43	29.76
	Greedy	32.08	145.30	254.39	19.73	27.84	256.36	379.26	21.70
	UGD	**16.36**	**95.96**	**223.77**	**44.98**	**19.98**	**180.27**	**281.72**	**32.421**



(a) Inference time comparison (s) (left: Porto, right: Xian) **(b) Throughput comparison (/s$\times$ 10^4) (left: Porto, right: Xian)**

Figure 5: The efficiency comparison of inference time and throughput.

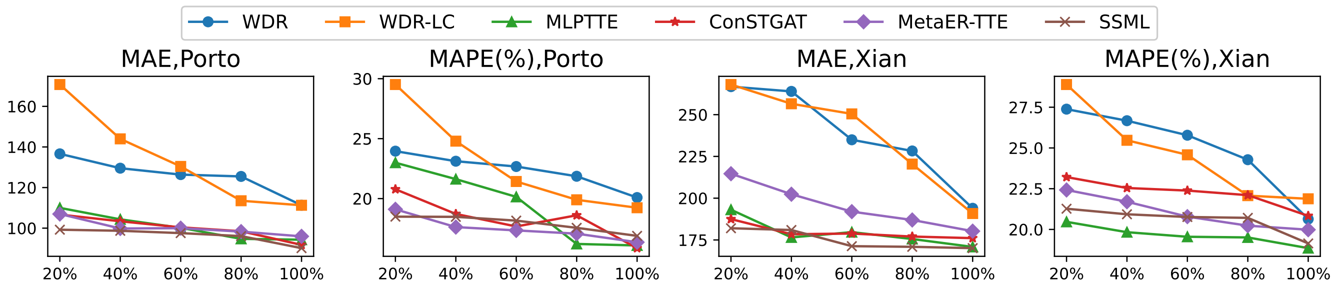


Figure 6: MAPE & MAE vs. the Scalability.

5.6 Online Test

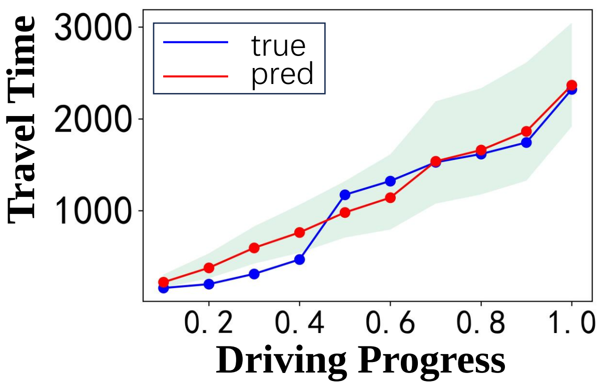
We conduct an online test simulation on the Xian dataset with the framework incorporating SSML as the backbone model. For the simulation, we select 100 routes that include temporal features (such

Table 2: Backbone complexity analysis. n refers to the number of segments, h refer to the feature dimensions.

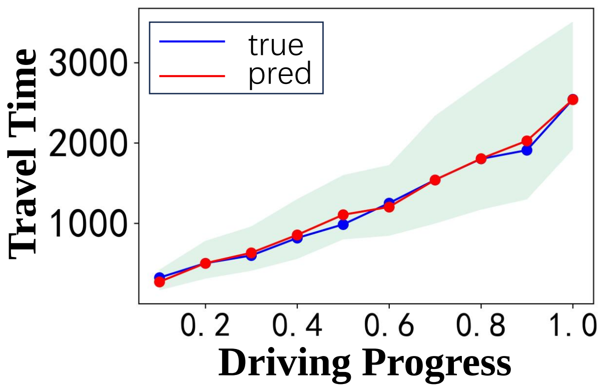
Method	Complexity	Components
MLPTTE	$O(nh^2)$	MLP
WDR	$O(nh^2)$	RNN
WDR-LC	$O(nh^2)$	RNN
ConSTGAT	$O(n^2h)$	Attention
SSML	$O(n^2h)$	Attention
MetaER-TTE	$O(n^2h)$	Attention

Table 3: Ablation study on the FTML and replace quantile regression to MIS.

Dataset	Model	MAPE	MAE
Porto	w/o FTML	17.58	94.43
	MIS	18.46	96.88
	Qua+FTML	**16.89**	**90.15**
Xian	w/o FTML	20.36	176.81
	MIS	24.75	228.07
	Qua+FTML	**19.14**	**170.10**



(a) Xian Oct. 2nd 15:39 2322s



(b) Xian Oct. 14th 23:06 2544s

Figure 7: Visualization of our framework in ER-TTE process. (The title of each subfigure is labeled in the form of "City, Date, Departure time, and Travel time".)

as weekdays/weekends) and spatial features (such as short/long distances). To evaluate the online efficiency, we divide per route to $k = 10$ parts, based on the proportion of the route driven (10% intervals). Before departure, the model generated confidence intervals for the entire route, At each 10% interval (from 10% to 90%), ER-TTE requests were made. Every route will have 9 queries during the route (10%-90%). Normally, this would result in 900 requests (9 queries per route × 100 routes). However, our framework reduced this to 334 requests, significantly improving efficiency and throughput.

Figure 7 illustrates the relationship between travel time and route completion percentage for two routes. In the left figure, only 3 initial requests needed re-estimation when actual travel times deviated from predicted confidence intervals, primarily due to holiday traffic in Xian and initial acceleration phases. In contrast, the right figure, which depicts late-night travel, did not require any re-estimations due to stable traffic conditions. These results demonstrate that our framework can efficiently adapt to varying traffic conditions, initiating re-estimations only when necessary, thereby ensuring flexibility and efficiency.

6 CONCLUSION

In this paper, we present a general framework that enhances ER-TTE by integrating UGD and FTML. This framework achieves efficient and effective ER-TTE—a previously unexplored area. UGD plays a pivotal role by providing confidence intervals that guide the system in deciding whether re-estimation is necessary, optimizing the use of computational resources. FTML significantly enhances the effectiveness by learning the general drive patterns and adapting to specific tasks. This framework not only advances the state-of-the-art in ER-TTE but also offers a practical and scalable solution for improving system efficiency and effectiveness.

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