MultiCalib: National-Scale Traffic Model Calibration in Real Time with Multi-source Incomplete Data

Desheng Zhang
zhang@cs.umn.edu
University of Minnesota, USA

Fan Zhang
zhangfan@siat.ac.cn
SIAT, Chinese Academy of Sciences

Tian He
tianhe@cs.umn.edu
University of Minnesota, USA

Abstract

Real-time traffic modeling at national scale is essential to many applications, but its calibration is extremely challenging due to its large spatial and fine temporal coverage. The existing work mostly is focused on urban-scale calibration with complete field data from *single data sources* (e.g., loop sensors or taxis), which cannot be generalized to national scale, because complete single-source field data at national scale are almost impossible to obtain. To address this challenge, in this paper, we design MultiCalib, a model calibration framework to optimize traffic models based on *multiple incomplete data sources* at national scale in real time. Instead of naively combining multi-source data, we theoretically formulate a multi-source model calibration problem based on real-world contexts and multi-view learning. More importantly, we implement and evaluate MultiCalib with two heterogeneous nationwide vehicle networks with 340,000 vehicles to infer traffic conditions on 36 expressways and 119 highways, along with 4 cities across China. The results show that MultiCalib outperforms state-of-the-art calibration by 25% on average with same input data.

Categories and Subject Descriptors

H.4 [Information System Application]: Miscellaneous

Keywords

Incomplete Data, Model Calibration

1 Introduction

Traffic demand and supply modeling is essential for transportation management and planning [16]. A demand model assigns estimated traffic volumes to specific routes; whereas a supply model employs assigned traffic volumes to infer traffic speeds on routes based on a density-speed function [15]. These two kinds of models tie demand and supply together to determine temporal propagations of traffic flows. The resulting traffic conditions, such as travel times, delay, volumes, and speeds, are used for various planning and management applications, such as navigation and dispatching [18], to improve efficiency of daily transportation.

To increase accuracy of these models, a model calibration process is typically required where various parameters in traffic models are optimized based on real-world field data [5]. Many techniques [3] [10] [17] have been proposed

for demand/supply model calibration at *urban scale* based on field data, e.g., loop sensor data, camera data, or taxi GPS data. However, to our knowledge, there is little work, if any, on calibration on supply/demand models at *national scale*, which is essential for commercial logistics. Moreover, many applications require fine-grained traffic information, e.g., real-time navigation on road segment levels [19], which calls for model calibration at a spatiotemporal level of road segments and minutes. A national-scale coverage with fine-grained resolutions poses a new challenge for us, which cannot be addressed by existing urban-scale model calibration. This is because they typically employ data from *single sources*, e.g., loop sensors [4] or commercial vehicles such as taxis [11], with satisfactory urban-scale coverages and resolutions. But for the national-scale fine-grained calibration, these single-source data are often incomplete, which lead to a significant bias as shown in our motivation section.

In this work, we argue that with the recent advance of intelligent transportation systems, many vehicle networks at national scale are equipped with GPS and cellular devices, which enable national-scale traffic data collection without dedicated infrastructures, e.g., loop sensors or traffic cameras. It provides us an unprecedented opportunity to capture traffic dynamics from *national-scale multiple sources*. Therefore, in this paper, we combine two national-scale vehicle networks (e.g., both commercial and private vehicles) as a nationwide system, and employ their real-time data to calibrate models for national-scale logistics of our data providers. This approach is technically challenging because (i) isolated national-scale vehicle networks (either commercial or private) are still limited in spatiotemporal coverages due to their operational characteristics, and thus leads to *incomplete data*; (ii) naively combining data sources from multiple networks together has a bias against general traffic flows, which leads to *overfitting* of the calibration process, as shown by our motivation section.

To address these challenges, we propose a modeling and calibration framework called MultiCalib for national-scale real-time traffic with two novel techniques: (i) we address overfitting of naive multi-source model calibration based on *convex multi-view learning* with an iterative online process, and (ii) we improve data completeness of data sources at national scale by *context-aware tensor decomposition* with three extracted contexts. A novel combination of the above two techniques makes our work significantly different from previous model calibration where traffic models are often calibrated by complete urban-scale data from single sources. Further, MultiCalib is a generic technique independent from specific models, and can be applied to a wide range of models for our data providers to improve their data completeness and model accuracy. Our key contributions are as follows:

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SIGSPATIAL'16, October 31–November 03, 2016, Burlingame, CA, USA
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ACM 978-1-4503-4589-7/16/10...\$15.00
<http://dx.doi.org/10.1145/2996913.2996918>

- We design the first generic framework MultiCalib for traffic model calibration based on real-time multi-source data at national scale. To our knowledge, the proposed framework has two unique features: (i) it captures two kinds of heterogeneous vehicle systems at national scale, i.e., commercial and private, which provides valuable diversity; (ii) it has one of the largest quantitative and spatiotemporal coverages, i.e., 340,000 vehicles spanning over an area of 6 million km² for 12 months.
- We formulate convex multi-view learning based on multi-source data to address biases of traffic model calibration with single-source data. In particular, we optimize parameters for both demand and supply models by minimizing an objective function that measures overall weighted deviation from model outcomes to the ground truth. To efficiently solve this optimization, we design an iterative learning process to alternatively update model parameters and weights assigned to different data sources until no further improvement can be made for the objective function. We formally prove the convexity and convergence of our optimization.
- We design context-aware tensor decomposition based on real-time contexts and historical data to improve completeness of field data at fine-spatiotemporal granularity for the calibration. In particular, we extract three novel contexts, i.e., a temporal pattern and a spatial pattern for historical traffic info, along with vehicle density, for joint tensor decomposition.
- We implement a state-of-the-art model and calibrate it based on MultiCalib with 3TB data from two national-scale vehicle systems with 340,000 vehicles. We evaluate MultiCalib with 36 expressways and 119 highways, along with 4 cities, i.e., Beijing, Shanghai, Guangzhou and Shenzhen across China. The results show that compared to state-of-the-art calibration, MultiCalib increases model accuracy by 25% on average.

2 Motivation

To show our motivation, we first investigate spatiotemporal coverages of single-source data at national scale, and then explore the potential of multi-source data.

2.1 Single-Source Data Coverage

As in Fig. 1, we select one of major expressways in China called JingGang’Ao coded G4. It has a length of 2283KM with 2384 road segments, crossing 5 provinces in China, and connecting Beijing to several major cities in the southern part of China, e.g., Wuhan, Changsha, Guangzhou, and Shenzhen. With two national-scale commercial and private vehicle networks with 340,000 vehicles (details in Section 3), we investigate spatiotemporal coverages of them on G4 along with its origin Beijing and destination Shenzhen.

Specifically, we divide 24 hours into a total of 288 5-min slots, and for a particular slot, we calculate the one-week average percentage of road segments with at least one GPS point from a particular vehicle network among all road segments on G4 and these two cities as shown in Fig. 2. (i) During the daytime, both networks’ coverage percentages

Fig 1. G4 Expressway

Fig 2. Daily Coverage

are better than those of the early morning and late night. For the morning rush hour, the coverage percentages for private and commercial vehicles increase significantly; whereas for the evening rush hours, they decrease gradually. One possible explanation is the morning commutes are more regular than the evening commutes. (ii) The private vehicles have higher coverage percentages than the commercial vehicles, due to their large volume (295 thousand vs. 45 thousand). But the difference is not significant due to the long travel duration of commercial vehicles. The commercial vehicle network has a more stable coverage percentage through the daytime because commercial vehicles such as logistic trucks have a stable travel time schedule compared to private vehicles even during the late night. (iii) In general, both vehicle networks have incomplete data issues shown by the percentages of covered road segments. For example, among a total of 288 5-min slots, the private vehicle network can only cover 45% of all road segments at most; whereas the commercial vehicle network can only cover 34% of all road segments at most. On average, the commercial vehicle network has a coverage percentage of 29.3% and the private vehicle network has a coverage percentage of 36.8%, both of which lead to incomplete data issues for model calibration [5].

2.2 Multi-Source Data Coverage

In this work, we argue that as a promising solution to incomplete data issues, combining these two heterogeneous vehicle networks together can provide a better coverage from complementary perspectives due to their own operational features. As shown by the red curve in Fig. 2, we show the coverage percentage of a virtual vehicle network consisting of both private and commercial vehicles. We found that combining them provides valuable diversity in terms of coverages, e.g., the maximum coverage is close to 60% and the average coverage is 51.4%, which is an encouraging coverage percentage due to the large spatial area at fine temporal intervals. Nevertheless, because of different purposes of private and commercial vehicles, naively combining them together may lead to overfitting of model calibration [23]. Therefore, we propose a framework in this paper to *intelligently* integrate multiple national-scale systems together to increase their coverage percentages for national-scale model calibration as introduced in the next section.

3 National-Scale Model Calibration

In this section, we first present the architecture of MultiCalib, and then introduce its frontend physical systems, and finally shows its backend traffic modeling and calibration.

Fig 3. Daily National Coverage

3.1 MultiCalib Architecture

In MultiCalib, we use a set of national-scale systems for national-scale traffic demand/supply modeling and their calibration. From a broad perspective, we treat individual components, i.e., vehicles, in these systems as probing sensors in MultiCalib to sense traffic conditions at national scale in real time. Built upon an integration of two national-scale systems, MultiCalib provides unseen national dynamics under extremely fine spatiotemporal resolutions to support real-world applications, which cannot be achieved by any systems with single data sources in isolation, *e.g.*, a monolithic urban-scale infrastructure such as a taxi network.

Fig 4. MultiCalib Architecture

In Fig. 4, we outline MultiCalib with three components, *i.e.*, physical systems, model calibration, and data inference, providing a road map for the paper. (i) In Section 3.2, we introduce two national-scale vehicle networks as concrete frontend systems along with their data, and then in Section 3.3, we show our backend data-driven calibration; (ii) In Section 4, we explore multi-source data from these systems to calibrate traffic models based on iterative convex multi-view learning; (iii) In Section 5, for better calibration, we improve incomplete data of individual systems by context-aware tensor decomposition where we extract three contexts for joint decomposition; Finally, we deliver our model and results to logistic companies for their dispatching to provide positive feedback to their fleet.

3.2 Frontend Physical Systems

We have been collaborating with several logistics companies for both commercial and private networks and accessing their data feeds to obtain status of vehicles. In this version of MultiCalib implementation, we consider two vehicle networks, which detect national-scale traffic dynamics from complementary perspectives. Fig. 3 gives a China highway and expressway map, along with one-day coverages of these two networks by a density-based visualization we made during our implementation where the lighter the area, the higher the vehicle density. As we can see, both of them cover major cities in China such as Beijing, Shanghai, and Shenzhen, along with major highways such as 7 major radial expressways coded from G1 to G7.

For the private vehicle network, it has 295 thousand vehicles, which are used to detect real-time traffic at national scale by private vehicles. Their data are collected through onboard devices installed inside vehicles, which are mainly used for navigation purposes. We access these data through a navigation service provider to which every involved vehicles upload their real-time status to a cloud server by a cellular network. The private vehicle users can choose to opt out this optional data uploading service, but most users still upload data in order to access navigation services with real-time traffic info. One day data collected from all private vehicles in the network are about 9 GB with an average uploading interval of 10 seconds when devices are turned on.

For the commercial vehicle network, it has 45 thousand vehicles, which are used to detect real-time traffic by commercial vehicles. Their data are also collected through onboard devices and a cellular network, which are mainly used for monitoring and fleet management. We access these data through a logistic management company, which operates a fleet of commercial freight vehicles traveling on major national highways and expressways in China. Every vehicle uploads its real-time GPS locations and speeds back to a company's server as long as its engine is on, and then data are routed to our server. One day data collected from all commercial vehicles in the network are about 7 GB with an average uploading interval of 15 seconds.

The above two systems are extremely valuable for national traffic modeling and calibration. More importantly, they are spatiotemporally complementary to each other due

to their own purposes. In particular, the private vehicles cover almost all major cities in China, along with 119 national highways and 36 national expressways in China, but the average accumulated uploading duration for these private vehicles is 100 mins on average for one day due to the purpose of personal usage, e.g., daily commutes and occasional long-distance travels, instead of frequent long-distance travels. In contrast, the commercial vehicles only cover major cities and highways in China, but due to their commercial purposes, their average accumulated uploading time is 8 hours on average for one day. As a result, the private vehicles have better spatial coverages; whereas the commercial vehicles have better temporal coverages, which leads to complementary features for national-scale modeling and calibration.

Beginning Date	2015/1/1	Total Data Size	3 TB
Private Vehicle Network		Commercial Vehicle Network	
# of Vehicles	294,849	# of Vehicles	45,237
# of Daily Records	240 million	# of Daily Records	85 million
Format		Format	
Device ID	Date&Time	Plate ID	Date&Time
Direction	GPS&Speed	Odometer	GPS&Speed

Fig 5. National-scale Datasets

We briefly introduce our data management due to space limitation. Based on collaboration with these service providers, we establish a reliable and secure data transmission protocol, which feeds our server in Shenzhen Institutes of Advanced Technology with the above data collected by service providers with a wired connection. As in Fig. 5, together with service providers, we have been storing a large amount of data from these two systems to build historical and real-time models to monitor traffic conditions in order to provide better real-time services, e.g., navigation, along with data from other infrastructures such as loop sensors. For daily management and processing, we employ a 34 TB Hadoop Distributed File System (HDFS) with a cluster consisting of 11 nodes, and each of them is equipped with 32 cores and 32 GB RAM. For the software, we use the MapReduce-based Pig and Hive. Due to the large size of our data, we have been tracking down several kinds of errant data, e.g., data with logical errors, duplicated data and missing data. Thus, we have been conducting a data cleaning process to filter out errant data on a daily basis. We protect the privacy of private and commercial vehicle users by (i) generating models based on aggregated anonymized data, which cannot be used to trace back to individual drivers; (ii) only processing information related to traffic and drop all other information such as odometer readings and cruising ranges.

In short, our endeavor of consolidating the above multi-source data from complementary physical systems enables national-scale real-time phenomenon rendering, which is unprecedented in both quantity and quality. We use them to implement MultiCalib to perform national-scale modeling and calibration for our data providers as introduced next.

3.3 Backend Modeling and Calibration

Based on the data from frontend physical systems, we generate and calibrate traffic models to capture national-scale traffic condition in our backend server. Given the existence of a plethora of traffic models [4] [7] [20], we decide

to focus on calibration of existing models, instead of designing new models. Next, we briefly give some preliminaries of traffic demand and supply modeling, along with existing calibration based on single-source data.

3.3.1 Existing Demand and Supply Models

The demand model is also known as route choice models. The input of a demand model is an origin-destination (OD) matrix X_t for a particular time interval t based on OD estimation; its output is vehicle density $D_{t,s}$ for a road segment s during a time slot t . In particular, we use one of the most common demand models as an example [7] to show the details of a demand model as follows.

1. Simulating behaviors of individual drivers with a fixed OD matrix by selecting a particular route r (consisting of multiple segments) from a route candidate set $\mathcal{R}$ generated by a road network with a probability P_r , e.g.,

$$P_r = \frac{\exp(U_r + \beta_{t,r}^1 \cdot CF_r)}{\sum_{l \in \mathcal{R}} \exp(U_l + \beta_{t,r}^1 \cdot CF_l)}, \quad (1)$$

where U is an utility function of a route, i.e., the benefit of selecting this particular route, e.g., reduced travel time; CF is the commonality factor and indicates similarity between a particular route and other routes, e.g.,

$$CF_r = \ln \sum_{l \in \mathcal{R}} \left(\frac{L_{rl}}{\sqrt{L_r \cdot L_l}} \right) \beta_{t,r}^2, \quad (2)$$

where L_r and L_l are the length of routes r and l , and L_{rl} are the common length between routes r and l . $\beta_{t,r}^1$ and $\beta_{t,r}^2$ are parameters to be estimated. We ignore temporal subscripts for U , CF and R for simplicity.

2. Aggregating trips at road segment level based on their specific routes to output a vehicle density $D_{t,s}$ for a road segment s during a time slot t .

The supply model is to take output of a demand model, i.e., $D_{t,s}$, as input, and then output traffic speeds at road segment level based on speed-density functions. One example of speed-density functions is

$$v_{t,s} = v_{t,s}^* \cdot \left[1 - \left(\frac{\max(0, D_{t,s} - \underline{D}_{t,s})}{D_{t,s}^{\text{jam}}} \right) \beta_{t,s}^3 \right] \beta_{t,s}^4, \quad (3)$$

where $v_{t,s}$ is the unknown speed on a road segment s during t ; $v_{t,s}^*$ is a given free flow speed; $\underline{D}_{t,s}$ is a given minimum density; $D_{t,s}^{\text{jam}}$ is a given jam density, i.e., the extreme density associated with completely stopped traffic on s during t . $\beta_{t,s}^3$ and $\beta_{t,s}^4$ are parameters to be estimated. Based on a supply model, we have an expected speed $v_{t,s}$ to infer congestion.

3.3.2 Model Calibration by Single-Source Data

The existing model calibration is to adjust parameters of models based on urban-scale field data from single data sources such as loop sensors or taxis. Typically, calibration is presented in the form of an optimization problem, where an objective function based on goodness-of-fit measures is formulated. For example, one technique that calibrates demand and supply simultaneously is given as follows [6].

$$\min_{\mathcal{X}_t, \mathcal{P}_{t,s}} \mathbf{F} = \mathbf{D}_1(\bar{v}_{t,s}, v_{t,s}) + \mathbf{D}_2(\mathcal{X}_t^a, \mathcal{X}_t) + \mathbf{D}_3(\mathcal{P}_{t,s}^a, \mathcal{P}_{t,s}), \quad (4)$$

$$\text{s.t.}, v_{t,s} = \mathbf{M}(\mathcal{X}_t, \mathcal{P}_{t,s}).$$

where $\mathcal{X}_t$ is passenger demand; $\mathbf{M}$ is a demand/supply model. e.g., given in Eq.(3); $\mathcal{P}_{t,s}$ is a set of parameters in $\mathbf{M}$ (e.g., $\beta_{t,s}^1$ to $\beta_{t,s}^4$ in previous subsections); $\mathcal{P}_{t,s}^a$ and $\mathcal{X}_t^a$ are a-priori estimates for $\mathcal{P}_{t,s}$ and $\mathcal{X}_t$; $\mathbf{D}_1$, $\mathbf{D}_2$, and $\mathbf{D}_3$ are goodness-of-fit functions to measure a distance between two values; $v_{t,s}$ is the speed outputted by $\mathbf{M}$; $\bar{v}_{t,s}$ is the ground truth of the speed based on a single data source. The $\mathcal{X}_t$ and $\mathcal{P}_{t,s}$ that minimize $\mathbf{F}$ are selected as the optimal parameters.

However, in this paper, we argue that this kind of calibration works fine at urban scale where field data from single sources are complete for urban scale, but for our national-scale calibration, field data from single sources are often incomplete to obtain $\bar{v}_{t,s}$ as shown by our motivation section. Moreover, naively combining multiple data sources may improve completeness of field data, but it also introduces biased info leading to overfitting of calibration due to distinct natures of different data sources [23]. As follows, we first design a calibration technique by multi-view learning driven by multi-source data to address overfitting in Section 4, and then design a data inference technique by tensor decomposition to improve data completeness in Section 5.

4 Multi-View Model Calibration

In this section, we first formulate an optimization problem for multi-view calibration in Section 4.1, and develop an iterative process to solve this optimization in Section 4.2, and analyze calibration performance in terms of convexity and convergence in Section 4.3.

4.1 Calibration Optimization

The objective of our multi-view calibration is to obtain optimized parameters for given demand/supply models for a time period based on multiple streaming datasets from multiple systems. The calibration is given as follows.

- A demand/supply model $\mathbf{M}$ is given with a parameter set $\mathcal{P}_{t,s}$ to output the estimated speed $v_{t,s}$ for each road segment s during a time slot t ;
- A input demand set $\mathcal{X}_t$ is given in the form of dynamic origin-destination (OD) matrices;
- A-priori estimates for the model parameters in $\mathcal{P}_{t,s}$ and $\mathcal{X}_t$ are given as $\mathcal{P}_{t,s}^a$ and $\mathcal{X}_t^a$;
- K individual systems generate K field datasets from K different views in terms of traffic speed $\bar{v}_{t,s}^k, \forall k \in [1, K]$, which are improved by our tensor-decomposition-based data inference introduced next. Note that in our implementation, we set $K = 2$ because we have only 2 data sources, i.e., commercial and private vehicle networks.

Based on Eq. (4), we formulate an optimization problem to calibrate a given demand/supply model by optimizing its parameter set $\mathcal{P}_{t,s}$ for a particular road segment s .

$$\min_{\mathcal{X}_t, \mathcal{P}_{t,s}, \mathcal{W}_{t,s}} \mathbf{F} = \sum_{k=1}^K [w_{t,s}^k \cdot (\mathbf{D}_1(\bar{v}_{t,s}^k, v_{t,s}) + \mathbf{D}_2(\mathcal{X}_t^a, \mathcal{X}_t) + \mathbf{D}_3(\mathcal{P}_{t,s}^a, \mathcal{P}_{t,s}))],$$

$$\text{s.t.}, v_{t,s} = \mathbf{M}(\mathcal{X}_t, \mathcal{P}_{t,s}); \mathbf{R}(\mathcal{W}_{t,s}) = 1.$$

where $\mathcal{W}_{t,s} = \{w_{t,s}^1, \dots, w_{t,s}^K\}$ is a set of parameters to decide weights of particular data-driven views. $\mathbf{D}_1$, $\mathbf{D}_2$ and $\mathbf{D}_3$ are goodness-of-fit functions to measure a distance between two values; $\mathbf{R}(\mathcal{W}_{t,s})$ is a constraint function, which gives the distribution of view weights. Without this constraint, the optimization problem is essentially unbounded. For the sake of simplicity, we set $\mathbf{R}(\mathcal{W}_{t,s}) = 1$. Therefore, $\mathbf{F}$ indicates the overall weighted distance between multiple observed traffic speeds to the model output, under consideration of a-priori estimates of $\mathcal{P}_{t,s}$ and $\mathcal{X}_t$. The rationale behind $\mathbf{F}$ is that for a view with a higher weight, we have a high penalty if the model output has a longer distance to the speed observed from this view; whereas for a view with a lower weight, we have a low penalty if the output has a longer distance to the speed observed from this view. Thus, to minimize the objective function, the model output relies on the views with higher weights. To solve this optimization, we aim to find the $\mathcal{X}_t$, $\mathcal{P}_{t,s}$ and $\mathcal{W}_{t,s}$ that minimize this overall weighted distance by an iterative learning process as introduced next.

4.2 Iterative Calibration

We develop an iterative learning technique based on the block coordinate descent. Since in our objective function we have three sets of parameters, i.e., a demand matrix $\mathcal{X}_t$, a model parameter set $\mathcal{P}_{t,s}$ and a view-weight parameter set $\mathcal{W}_{t,s}$, we aim to iteratively yet alternatively optimize these three sets of parameters until the final result converges. Specifically, we optimize the values of one parameter set to minimize the objective function while keeping the values of the other two parameter sets fixed, and then we continue this process by swapping the fixed parameter sets and the optimized parameter set until the result converges. We give a description of our iterative technique in Fig. 6.

Fig 6. Iterative Multi-View Calibration

We first initialize $\mathcal{W}_{t,s}$ based on the estimation, because it does not affect the final result given the property of the block coordinate descent. In Step 1, we find the optimal $\mathcal{W}_{t,s}$ that minimizes $\mathbf{F}$ by fixing initial $\mathcal{X}_t$ and $\mathcal{P}_{t,s}$ (given by $\mathcal{X}_t^a$ and $\mathcal{P}_{t,s}^a$). In Step 2, we find the optimal $\mathcal{P}_{t,s}$ that minimizes $\mathbf{F}$ by fixing the optimized $\mathcal{W}_{t,s}$ and initial $\mathcal{X}_t$. In Step 3, we find the optimal $\mathcal{X}_t$ that minimizes $\mathbf{F}$ by fixing the optimized $\mathcal{W}_{t,s}$ and $\mathcal{P}_{t,s}$. Next, we go back to Step 1 to optimize $\mathcal{W}_{t,s}$ again based on updated $\mathcal{P}_{t,s}$ and $\mathcal{X}_t$, and so on. Thus, this

process is iterative by alternatively optimizing $\mathcal{P}_{t,s}$, $\mathcal{W}_{t,s}$ and $\mathcal{X}_t$ until the result converges. The convergence is based on the distance and constraint functions in $\mathbf{F}$ according to the property of the block coordinate descent [8]. As follows, we theoretically analyze the performance of this multi-view learning with respect to convergence.

4.3 Calibration Convergence

We use negative log function $\mathbf{R}(\mathcal{W}_{t,s}) = \sum e^{-w_{t,s}^k}$ as our constraint function of view weights. This is because it maps a number between 0 and 1 to a number from 0 to ∞ , which enlarges the difference between different view weights for better calibration. As for distance functions $\mathbf{D}_1$, $\mathbf{D}_2$ and $\mathbf{D}_3$, we use Normalized Squared Loss function given as $\mathbf{D}(\bar{v}_{t,s}^k, v_{t,s}) = \frac{(\bar{v}_{t,s}^k - v_{t,s})^2}{\text{STD}(\bar{v}_{t,s}^1, \dots, \bar{v}_{t,s}^K, v_{t,s})}$. This function is an effective method to measure a distance between two variables and at the same time consider the distribution of $\bar{v}_{t,s}^k$. As follows, we show the convexity and convergence of this iterative process given the constraint and distance functions.

THEOREM: If the above two functions are used, then convergence of the iterative calibration in Fig. 6 is guaranteed.

PROOF: Based on the convergence proposition on the block coordinate descent [8], if the optimizations in Steps 1, 2 and 3 are convex, then the iterative process will converge to a stationary point. For Step 1, we aim to prove that if $\mathcal{X}_t$ and $\mathcal{P}_{t,s}$ are fixed, the optimization for $\mathcal{W}_{t,s}$ is convex. We introduce a variable $z_{t,s}^k = e^{-w_{t,s}^k}$. Thus, the optimization becomes a new function with only one variable $z_{t,s}^k$. $\min_{z_{t,s}^1, \dots, z_{t,s}^K} \mathbf{F} = \sum_{k=1}^K [-\log(z_{t,s}^k) \cdot (\mathbf{D}(\bar{v}_{t,s}^k, v_{t,s}) + \mathbf{D}(\mathcal{X}_t^a, \mathcal{X}_t) + \mathbf{D}(\mathcal{P}_{t,s}^a, \mathcal{P}_{t,s}))]$ under a constraint $\sum_{k=1}^K z_{t,s}^k = 1$. Thus, we have a linear constraint function with this variable $z_{t,s}^k$, and a linear combination of negative log functions as the objective function. Both the constraint and objective functions are convex, so any local optimal solution is also the global optimal solution for Step 1. For the convexity of Steps 2 and 3, we can formulate the objective function with one variable as an unconstrained optimization. Since the distance function is convex in Steps 2 and 3, the objective function is also convex as they are a linear combination of convex functions. $\square$

This theorem indicates our iterative calibration process can quickly converge based on these two functions, which makes it suitable for real-time modeling and calibration.

5 Context-Aware Data Inference

In this section, we address a key practical challenge for multi-view model calibration introduced above, i.e., data incompleteness. Given national-scale and real-time requirements, data from neither private vehicle networks nor commercial vehicle networks are complete to serve as field data for multi-view calibration. Thus, we focus on improving single-source data by constructing a 3D tensor in Section 5.1, and extracting 3 contexts in Section 5.2, and performing our context-aware decomposition in Section 5.3.

5.1 Tensor Construction

We infer traffic speeds on particular road segments for specific time slots by a 3D tensor $\mathcal{A} \in \mathbb{R}^{N \times K \times M}$.

- A traffic speed dimension indicates traffic speed categories (e.g., 0-5 mph, 5-10 mph, etc): $[v_1, \dots, v_N]$.

- A temporal dimension indicates specific time slot (e.g., a 5-min slot from 0:00 AM to 0:05 AM): $[t_1, \dots, t_K]$.
- A spatial dimension indicates specific spatial units (e.g., a road segment in a nation highway): $[s_1, \dots, s_M]$.
- An entry $\mathcal{A}(n, k, m)$ indicates the number of GPS records given by a particular data source for a traffic speed category n in a spatial unit m during a slot k .

With either our private or commercial vehicle data, we fill this tensor $\mathcal{A}$, and then obtain a traffic speed distribution under a specific spatiotemporal partition. But a key challenge is that the tensor $\mathcal{A}$ is incomplete because of our fine-grained spatial-temporal coverage. For example, for a road segment without any vehicle in particular time slots, its corresponding entries are empty due to lacking GPS data.

Fig 8. Context-Aware Tensor Decomposition

A common approach by the machine learning community to address this data incomplete issue is to use tensor decomposition. For example, as in Fig. 8, we have a tensor $\mathcal{A}$ with these three dimensions. An entry denotes a tuple [speed, location, time]. But $\mathcal{A}$ is sparse due to fine spatiotemporal granularity, e.g., we may have millions of road segments under one minute slots. Thus, we can decompose $\mathcal{A}$ into a core tensor $\mathcal{I}$ along with other three matrices, $\mathcal{V} \in \mathbb{R}^{N \times d^v}$, $\mathcal{S} \in \mathbb{R}^{M \times d^s}$, and $\mathcal{T} \in \mathbb{R}^{K \times d^t}$, based on the Tucker decomposition model [14]. $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{T}$ infer correlations between different speed categories, different spatial units, and different time slots, respectively. d^v , d^s and d^t are the numbers of latent factors and very small. The following objective function is often used to optimize the above decomposition by minimizing the decomposition error.

$$\min_{\mathcal{I}, \mathcal{V}, \mathcal{S}, \mathcal{T}} \mathbf{L}(\mathcal{I}, \mathcal{V}, \mathcal{S}, \mathcal{T}) = \mathbf{D}_4(\mathcal{A}, \mathcal{I} \times \mathcal{V} \times \mathcal{S} \times \mathcal{T}),$$

where $\mathbf{D}_4$ usually is a l_2 -norm-based measurement, e.g., $\|\mathcal{A} - \mathcal{I} \times \mathcal{V} \times \mathcal{S} \times \mathcal{T}\|^2$. By minimizing this objective function, we obtain optimized $\mathcal{I}$, $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{T}$ by the sparse tensor $\mathcal{A}$, which is given by real-time GPS data from either private vehicle networks or commercial vehicle networks. As a result, we use $\mathcal{I} \times \mathcal{V} \times \mathcal{S} \times \mathcal{T} = \mathcal{A}'$ to approximate $\mathcal{A}$ where $\times$ is the tensor-matrix multiplication.

However, in this work, we have a new challenge, i.e., $\mathcal{A}$ is over sparse at national scale with either private or commercial vehicles as shown in our motivation section, which leads to poor performance of traditional decomposition. To

Fig 7. Three Cities for Implementation and Evaluation

address this issue, we design a technique to use historical GPS data to establish several correlated contexts for context-aware tensor decomposition as follows.

5.2 Real-world Contexts

We use historical data to establish 3 contexts to provide additional info for our decomposition, i.e., temporal/spatial patterns for historical traffic, along with vehicle density. To formulate 3 contexts, we design 3 matrices as in Fig. 8.

- Vehicle Densities as in a matrix $\mathcal{B}$ where a row denotes a spatial unit; a column denotes a slot; an entry denotes the average vehicle count in this spatial unit for this slot over a period of time.
- Spatial Patterns for Speed as in a matrix $\mathcal{C}$ where a row denotes a spatial unit; a column denotes a speed category; an entry denotes the number of GPS records in this speed category and this spatial unit over a period of time.
- Temporal Patterns for Speed as in a matrix $\mathcal{D}$ where a row denotes a slot; a column denotes a speed category; an entry denotes the number of GPS records in this speed category and this slot over a period of time.

All $\mathcal{B}$, $\mathcal{C}$, and $\mathcal{D}$ are obtained with historical GPS data.

5.3 Context-aware Tensor Decomposition

With the extracted contexts, we design joint context-aware decomposition with an objective function as follows.

$$\begin{aligned} \min_{I, \mathcal{V}, \mathcal{S}, \mathcal{T}} \mathbf{L}(I, \mathcal{V}, \mathcal{S}, \mathcal{T}) &= \mathbf{D}_4(\mathcal{A}, I \times \mathcal{V} \times \mathcal{S} \times \mathcal{T}) \\ &+ \mathbf{D}_4(\mathcal{B}, \mathcal{S} \times \mathcal{T}) + \mathbf{D}_4(\mathcal{C}, \mathcal{S} \times \mathcal{V}) + \mathbf{D}_4(\mathcal{D}, \mathcal{T}^T \times \mathcal{V}), \end{aligned} \quad (5)$$

where the $\mathbf{D}_4$ usually is the l_2 norm; the first term measures

decomposition errors about $\mathcal{A}$; the next three terms measure the error of factorizing matrices $\mathcal{B}$, $\mathcal{C}$, and $\mathcal{D}$. In this function, $\mathcal{A}$ and $\mathcal{B}$ share $\mathcal{S}$ and $\mathcal{T}$; $\mathcal{A}$ and $\mathcal{C}$ share $\mathcal{S}$ and $\mathcal{V}$; $\mathcal{A}$ and $\mathcal{D}$ share $\mathcal{V}$ and $\mathcal{T}$. Since $\mathcal{B}$, $\mathcal{C}$, and $\mathcal{D}$ are obtained by historical data, they lead to accurate $\mathcal{S}$, $\mathcal{T}$ and $\mathcal{V}$, which improve decomposition of $\mathcal{A}$ itself. Thus, the historical traffic speed patterns are transferred into the decomposition of $\mathcal{A}$, which leads to better tensor decomposition for sparse tensors.

For the decomposition purpose, we first normalize all values to $[0, 1]$ and set $d^v = d^s = d^t$. Next, we use an element-wise optimization algorithm as a numeric method [13] to obtain a local optimal solution for I , $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{T}$, since this objective function does not have a closed-form solution to find the global optimal solution. Finally, after we obtain I , $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{T}$, we use $I \times \mathcal{V} \times \mathcal{S} \times \mathcal{T} = \mathcal{A}'$ to obtain complete tensors for both private and commercial vehicle networks as complete field data for multi-view model calibration.

6 Implementation and Evaluation

We test MultiCalib based on our data in Fig. 5. Along with service providers from whom we have data access, we implement MultiCalib on 36 expressways and 119 highways in China as in Fig. 3, together with four major cities in China, i.e., Beijing, Shanghai, Guangzhou and Shenzhen, to gain insights for their national-scale dispatching. As in Fig. 7, we create a visualization of our implementation for three cities where we found that the commercial vehicles are mostly focused on major expressways, and the private vehicles are more evenly distributed around landmarks in the cities. In particular, we investigate MultiCalib on these cities' roads classified as motorways in OpenStreetMap [2], which are highest-performance roads, e.g., in Shenzhen, we have 564 segments classified as motorways.

We compare MultiCalib with one state-of-the-art calibration technique called OC-DTA [6], which is an efficient model calibration on the classic supply/demand model called DynaMIT [7] based on single-source data. We aggregate GPS data from both vehicle networks to feed OC-DTA for a fair comparison. OC-DTA serves as a naive multi-source approach for model calibration where multiple data sources are combined straightforwardly. In contrast, MultiCalib uses multi-view-learning-based calibration with tensor decomposition for multi-source calibration.

We use cross-validation to evaluate the performance of MultiCalib with 13 weeks of data. We divide the 13 week dataset in Fig. 5 into two subsets: one as a testing dataset containing data about a particular day, e.g., day d_1 , and it is used to serve as the real-time streaming data; the other as a historical dataset containing data about the rest of days, serving as the historical training data for demand and supply models. If we use 5-min slots for modeling, for the first slot t_1 , i.e., from 00:00 to 00:05, with the vehicle data in the historical training dataset, we use MultiCalib to calibrate a traffic model to find the optimal model parameters for all road segments in this slot. Then, we use the testing dataset (which gives us traffic speeds of a particular day) as the ground truth to verify the calibrated model. For some cities and highways, e.g., Shenzhen and G4, we have loop detector data to serve as the ground truth, which are inductive loops installed in selected major road segments and can detect metal and thus accurately detect vehicle speeds. We let the testing dataset rotate among all data, leading to multiple sets of experiments. The average results are reported.

We test the MultiCalib with Mean Average Percent Error (MAPE) as $MAPE = \frac{100}{n} \sum_{i=1}^n \frac{|\bar{v}_i - v_i|}{\bar{v}_i}$, where n is the total number of temporal-spatial combinations we tested. e.g., under 10 min slots, we have $24 \times \frac{60}{10} \times (36 + 119) \times 1250 = 2790000$ combinations for a one-day evaluation given we have $(36+119)$ routes and 1250 segments per route. Under a temporal-spatial combination i , v_i is the traffic speed inferred by a calibrated model, while $\bar{v}_i$ is the ground truth. An accurate calibration yields a small MAPE, and *vice versa*.

We first show results in four cities and four particular expressways from G1 to G4, along with the average result on all highways. Then, we study impacts of slot lengths. Further, we investigate the impact of historical data sizes on the running time and the accuracy of MultiCalib to show its feasibility and robustness for real-world calibration. Finally, we present an evaluation summary.

6.1 Impact of Cities

Fig. 9-12 plot the average MAPE under 5-min slots for all motorways in Beijing, Shanghai, Guangzhou, and Shenzhen, respectively. In general, we found that MultiCalib has better performance than OC-DTA, e.g., in Beijing, MultiCalib outperforms OC-DTA by 28%. This is because OC-DTA only naively uses multi-source GPS data to calibrate traffic models without data inference and multi-view perspectives; whereas MultiCalib uses a data inference technique to improve the completeness of data and then uses a multi-view-learning-based calibration to optimize the model. For all cities, we found the performance of calibration becomes

better for both techniques in the morning and evening rush hour, because there are abundant field data to calibrate the model during that time with low speeds. But for the early morning or late night, their performance becomes worse due to incomplete field data. As for Beijing, the variation of calibration performance is larger than Shanghai and Guangzhou, e.g., during the evening rush hour, the MAPE in Beijing is close to 5%, but for the early morning its MAPE is up to 29%. It may be because of the heavy traffic flow in Beijing compared to other cities. For Shenzhen, the MAPE becomes lower starting at the early afternoon compared to others, which indicates a different pattern for the evening rush hour in Shenzhen. For the morning rush hour, all cities's performance becomes the best around 8AM, which is the most crowded hour in many cities.

Fig 9. Beijing

Fig 10. Shanghai

Fig 11. Guangzhou

Fig 12. Shenzhen

6.2 Impact of Expressways

Fig. 13-16 plot the average MAPE under 5-min slots for all major road segments in China national expressway G1, G2, G3, and G4, respectively. Their maps are given in Fig. 3. We also found that MultiCalib outperforms OC-DTA in general. But the main difference between the calibration on national expressways and cities is that there are no clear morning and even rush hours in expressways. Typically, for all expressways, the performance of calibration for both techniques becomes better from 6AM and worse from 10PM. One of the possible explanations is that during these time periods, the field data are more complete due to a large number of vehicles on the expressways, which leads to better calibration. For G1 connecting Beijing to Harbin, MAPE is smooth during the daytime, which may be because it has a short distance and is the only expressway to the northeastern part of China, thus leading to heavy traffic. For G2 connecting Beijing to Shanghai, MAPE is also smooth during the daytime but with some effects of the evening rush hour, because it connects two biggest cities in China. For G3 connecting Beijing to Fuzhou (with future planning to Taiwan), MAPE is higher during the noon or afternoon, which may be because of limited number of vehicles on this expressway due to its

current construction and no major cities in the middle of G3. For G4 connecting Beijing and HongKong, MAPE is lower in the morning rush hour, the late afternoon and the early evening due to heavy traffic on this major expressway with several big cities with tens of millions of people.

Fig 13. G1 Expressway

Fig 14. G2 Expressway

Fig 15. G3 Expressway

Fig 16. G4 Expressway

Fig. 17 gives the average MAPE for all 119 national highways and 36 expressways under 10-min slots during 24 hours. The MAPE of both calibration techniques are typically higher than the MAPE we found from Figs. 13 to 16. This is because the data coverage percentage may change dramatically between different highways, and some highways with few vehicles uploading GPS data lead to higher MAPE. But the relative performance between the two calibration techniques is similar. MultiCalib has an average MAPE of 17.2%, while OC-DAT has an average MAPE of 23.2%, which leads to a 25% performance gain for MultiCalib. The performance gains are more obvious in the early morning, which may result from our inference technique.

Fig 17. Average MAPE

Fig 18. Effects of Lengths

6.3 Impact of Slot Lengths

Fig. 18 plots the both MAPE with different slot lengths with a default value of 5 mins. The MAPE of both calibration techniques decreases with the lengths of the time slots. This is because in a longer slot more data about vehicles can be accumulated to infer traffic speeds, and also the traffic speed becomes more stable. MultiCalib outperforms OC-DTA significantly if the slot is shorter than 20 mins because MultiCalib uses a data inference technique to improve this data completeness. This advantage is more obvious during

short time slots where data are more incomplete. But when the slot becomes longer than one hour, both techniques have similar performance. This is because in such a long slot, we have enough data for calibration of relatively stable speeds.

6.4 Impact of Historical Data

We study the impact of historical data on model accuracies and running time by comparing MultiCalib to OC-DTA with a default value of 13 weeks. Figs. 19 and 20 plot running time and MAPE on different lengths of historical data in terms of weeks. As expected, the more the historical data, the longer the running time, the more accurate the model calibration, the lower the MAPE. MultiCalib has 15% longer time than OC-DTA, which in turn leads to a 25% lower MAPE. This is because MultiCalib has to perform its tensor decomposition to infer incomplete data along with iterative calibration, which leads to longer running time.

Fig 19. History vs. Time

Fig 20. History vs. MAPE

6.5 Evaluation Summary

We have the following observations. (i) The calibration performance is highly dependent on both venues and time as shown by Figs. from 9 and 16. Every city or expressway has its own characteristics, which needs to be considered when modeling. On average, all techniques have better performance during the time when more data can be used for calibration as in Fig. 17. (ii) The length of slots significantly affects the performance of calibration as in Fig. 18. Normally, a longer slot has better performance than a shorter slot, but a longer slot has low usability in real-time applications. (iii) As in Figs. 19 and 20, MultiCalib has longer running time, but it increases its accuracy. (iv) Looking across factors, it seems spatiotemporal contexts have the highest impact, and then slot lengths, and finally historical data length.

7 Related Work

MultiCalib is related to traffic modeling and calibration as well as multi-source data-driven systems.

7.1 Traffic Modeling and Calibration

Traffic modeling and its calibration are very important for urban transportation and planning. Recently with the increasing availability of vehicle GPS data, numerous modeling and calibration techniques have been proposed for transportation services [18], e.g., inferring taxicab passenger demand [11] [12] [21], assisting regular drivers for route planning [20]; estimating traffic volumes or speeds [4]; assigning dynamic traffic to road segments [7]. To improve the performance of these models, several calibration techniques have also been proposed, e.g., jointly calibrating both demand and supply models [6]; online calibrating based on non-linear Kalman filtering [3]; offline calibrating based on sensitivity analyses [10]; calibrating based on fuzzy Bayesian

model [17]. These modeling and calibration techniques can be used by many applications, e.g., navigation and dispatching [18], to improve transportation efficiency.

However, all of the above work is for urban-scale modeling and calibration, and their key assumption is that single-source field data for modeling and calibration, e.g., loop sensors, camera data or taxi data, are complete [17]. But for national-scale modeling and calibration, this assumption cannot be held anymore, because we do not have single-source infrastructure at national scale to provide complete field data. In this work, from a multi-source data perspective, we investigate and improve incomplete data from two national-scale vehicle networks by a data inference technique based on context-aware tensor decomposition, along with multi-view-learning-based calibration. Under national-scale and multi-source data contexts, these two techniques make our work significantly different from previous traffic model calibration based on single-source data at urban scale.

7.2 Multi-source Data-driven Systems

Multi-source data-driven systems at large scale are considered rare because it is challenging to access or collect multi-source data for the same area. Based on our research impact, we have been collaborating with several service providers to access their data feeds and provide business insights for them based on our models in return. We have been working on several types of multi-source data-driven systems, e.g., urban mobility modeling [22] and urban traffic modeling [23], and sharing data for the benefit of research community [1]. Different from our previous work focusing on urban-scale phenomena, this paper is to use two national-scale vehicle networks to calibrate traffic models at national scale with 295 thousand private vehicles and 45 thousand commercial vehicles. To our knowledge, national-scale traffic modeling and calibration based on such large-scale diverse systems have never been performed before.

Technically, the key difference between our multi-view learning and classic multi-view learning, e.g., co-training [9], is that they did not consider different weights of different views. In contrast, we automatically assign weights to different views under a particular spatio-temporal combination to find the data-driven views that are more important for model calibration, instead of considering them equally.

8 Conclusion

In this work, we design and implement MultiCalib to effectively calibrate national-scale traffic models based on multi-source incomplete data in real time. Our efforts lead to a few valuable insights for fellow researchers to design and implement real-time data-driven models at national scale. Specifically, these insights are that (i) heterogeneous physical systems provide complementary data, which can be intelligently integrated together to improve the performance of modeling and calibration; (ii) even though field data are mostly incomplete to model national-scale phenomenon in real time, a data inference technique based on historical data and real-world contexts can improve completeness of data, thus enabling better modeling; (iii) instead of naively combining different data sources together, a weight-based modeling technique from multi-view perspectives leads to better

performance by an iterative measuring process.

9 Acknowledgements

This work was supported by US NSF Grants CNS-1446640 and CNS-1544887, and China 973 Program 2015CB352400, and Research Program Grants of Shenzhen.

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