Will there be a construction? Predicting road constructions based on heterogeneous spatiotemporal data

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ABSTRACT
Road construction projects maintain transportation infrastructures, and range from short- to long-term. Deciding what the next construction project is and when it is to be scheduled is traditionally done through inspection by humans using special equipment, which is costly and difficult to scale. An alternative is the use of computational approaches that integrate and analyze multiple types of past and present spatiotemporal data to predict location and time of future road constructions. This paper reports on such an approach, one that uses a deep-neural-network-based model to predict future constructions, based on a heterogeneous dataset consisting of construction, weather, map and road-network data. We also report on how we addressed the lack of adequate publicly available data by building a large scale dataset named “US-Constructions”, that includes 6.2 million road constructions augmented by a variety of spatiotemporal attributes and road-network features, collected in the contiguous United States (US) between 2016 and 2021. Extensive experiments on several major cities in the US show the applicability of our approach to accurately predict future constructions.

CCS CONCEPTS
- Computing methodologies → Supervised learning by classification; - Applied computing → Transportation.

KEYWORDS
US-Constructions, Road Constructions Prediction, Dataset

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1 INTRODUCTION
Road constructions are essential to maintaining transportation infrastructures with the annual cost of road constructions increasing from 87.9 billion dollars in 2017 to 100.4 billion dollars in 2021 - an increase of over 18% 1. This paper addresses the unique use of computational solutions to determine future constructions, rather than labor-intensive manual inspections or data-intensive image analysis [1, 2, 4, 18], telematics and vehicle probe data [8].

We begin by addressing data challenges by introducing a unique dataset of 6.2 million road constructions in the US between 2016 and 2021, along with their spatiotemporal context viz. location details, time, a brief human provided description, daylight and weather. We also describe our process for building this dataset. Researchers may either directly use our dataset or mimic our approach to build their own dataset. We also explore an important and useful research problem, that of “identifying future constructions from past constructions along with their spatiotemporal context (e.g., traffic, weather, and map imagery) for certain locations (represented by their geographical region hexagon – see Section 4) during specific time frames (e.g., the next 15 days). Our goal is to develop a cost-saving, coverage-enhancing approach complementary to current practices. For example, we see our approach as being used to quickly identify potential sites, which can then be evaluated by human inspection.

In our approach, we model heterogeneous spatiotemporal information using a deep-neural-network that combines recurrent and convolutional components. The convolutional component is used for extracting latent information from map imagery. The recurrent component models time-series data (e.g., traffic and weather) along with additional spatial information (e.g., features of the road-network) about a location. Our goal with this model is to predict the possibility of a construction event in the near term (specifically, the next 15 days). On average, our proposed model outperformed the best baseline model by 2.8% in F1-score, when tested over multiple major cities in the US. In summary, the main contributions of this paper are:

- **Dataset**: We introduce a new dataset of road constructions and closures for the continental US, with about 6.2 million cases from the years 2016 to 2021. To our knowledge, this is the first public dataset that offers this type and scale of data.
- **Model**: We present a deep-neural-network model to predict short-term constructions. Our model is capable of using heterogeneous data, and resulted in superior prediction outcomes when compared to the baseline models.

2 RELATED WORK
Previous related studies examined a variety of topics ranging from detection of road issues (such as cracks) [6], analysis of the maintenance of roads [9, 10, 16], road-closure detection [3, 14], and lifecycle analysis of roads [5, 7]. Tong et al. [17] employed deep convolutional neural network (DCNN) models for finding the length of cracks in asphalt pavement from gray-scale images. They classified images to 8 different classes according to the length of the crack and achieved an accuracy of 94.36%. Ye et al. [19] employed a convolutional neural network (CNN) model to identify potholes in asphalt pavements, by using a dataset of 400 images that were collected from different pavements under different lighting conditions. In another study Cheng et al. [3] presented a road closure detection framework based on multi-feature fusion. Their framework has two parts, an offline road closure feature modeling part and an online...
identification part. The offline modeling first partitions the road-network into grids, and then extracts closure features for the grids from historical data. The online component screens out closed grid candidates based on the plunge in traffic flow.

Our paper borrows concepts from the papers described above while tackling the different problem of predicting the possibility of a future construction event at a location. To our knowledge, this is the first study that seeks to solve a problem of this type using a purely computational approach. This work has real-world application, in that it can be used to find areas in need of maintenance. It is also cost-effective because it is based on analyzing already recorded and available information such as past road constructions, road-network features, weather data, and coarse-grained map images. As we show in this paper, the input data we employ is easy to collect and available to the public.

3 THE US-CONSTRUCTIONS DATASET

In this section, we describe the countrywide traffic construction dataset, which we have named US-Constructions, and the process to build it is shown in Figure 1. Details on steps 1 through 7 can be found in [12] (see the Dataset section), thus we only describe the last three steps in this section.

![Figure 1: Process of Building US-Constructions Dataset](image)

3.1 Augmentation with Road Class

Road class (e.g., primary, secondary, and motorway) is an important feature of the location of a construction. We used OpenStreetMap (OSM) to obtain this information and adopted its road classification system to annotate constructions. For a construction c, the goal is to find the most relevant road class based on its start and end locations. To do so, we first used “Nearest Service” OSRM API to find the nearest nodes to the location of c based on a 50 meters distance threshold. We then obtained “ways” on which the nearest nodes were located. Finally, we employed the OSM service “Full” to obtain road-class information for the ways, and used the most frequent road class to annotate c.

3.2 Augmentation with Average Road Speed

We obtain the average speed based on start and end locations of a construction (if both are available). We use the OSM “Route Service” to estimate a free-flow speed based on travel distance and time.

3.3 Augmentation with Closure Type

Some of the constructions result in road closures. We introduce a rule-based process to annotate each construction with a closure type, if there is one. We define three cases: road-closure, lane-closure, and no-closure. We use the human-provided description of each construction event, and employs several regular-expression patterns to infer the closure type. Examples of human-provided descriptions are “Closed due to roadwork”, “Closed for bridge demolition work”, “Roadway reduced to 1 lane”, “Three lanes closed due to construction work”, and “Intermittent lane closures due to utility work”.

From manual probing of the human-provided descriptions for a set of 10,000 randomly selected construction events we found 14 distinct patterns that represent closures. Of these patterns, four represent a road closure and ten of them a lane closure. Examples of these patterns are close* * roadwork, close* * bridge, * lane* block*, reduced * lane*, hard shoulder block*, and * shoulder close*. The full list of patterns is available in the long version of this paper on arXiv.

3.4 Final Dataset

The final dataset comprises 6.2 million construction records, collected between January 2016 and December 2021 in the continental United States, and is publicly available at https://www.kaggle.com/datasets/sobhamoosavi/us-road-construction-and-closures. Each construction record is described by 45 attributes as shown in Table 1.

![Table 1: US-Constructions Dataset](image)

4 RESEARCH QUESTION

Suppose we are given a set C of construction events, when c ∈ C is defined as c = (latitude, longitude, start_time, end_time, description, temperature, humidity, w_condition, severity, road_info, road_type). Here “description” is a human-provided description, temperature is in Fahrenheit, w_condition is the weather condition (e.g., rain,
snow, and clear), severity is an integer between 1 and 4, road_info
are additional details about the road (e.g., distance and average speed), and road_type is the OSM-based road type (or road-class).
Additionally, we have a database of geographical map images M consisting of hexagonal tiles with sufficient resolution, and a dataset of points-of-interest P (e.g., amenities, traffic lights, and stop signs) for a specific zone (or region) of the map. Given these datasets, we define our research question below.

Given:
- A set of spatial regions $R = \{r_1, r_2, \ldots, r_n\}$, where $r \in R$ is a hexagonal zone, according to the definition provided by Uber H3 library [15]. Here we choose a resolution level 7 which results in zones with edge size $1.2km$ and area $5.16km^2$.
- A set of fixed-length time intervals $T = \{t_1, t_2, \ldots, t_m\}$, where we set $|T| = 15$ days, for $t \in T$.
- A database of construction events $C_r = \{c_1, c_2, \ldots\}$ for $r \in R$.
- A database of map image data $M_r = \{m_1, m_2, \ldots\}$ for $r \in R$.
- A database of points-of-interest $P_r = \{p_1, p_2, \ldots\}$ for $r \in R$.

Create:
- A representation $F_{rt}$ for a region $r \in R$ during a time interval $t \in T$, using $C_r, M_r,$ and $P_r$.
- A binary label $l_{rt}$ for $F_{rt}$, where 1 indicates at least one traffic construction was reported during $t$ in region $r$; 0 otherwise.

Find:
- A model $M$ to predict $L_{rt}$ using $(F_{rt_{t-10}}, F_{rt_{t-9}}, \ldots, F_{rt_{t-1}})$, which means predicting the label of current time interval using observations from the last 10 time intervals.

Objective:
- Minimize the prediction error.

Note that we chose the size of regions and time intervals in order to address the sparsity of input data, while still building a viable model that could provide real-time insights.

## 5 MODEL

In this section we first describe the input data representation, and then our predictive model.

### 5.1 Feature Vector Representation

We create a feature vector representation for each hexagonal geographical region $r$ of resolution 7 during a time interval $t = 15$ days by aggregating input data. To be precise, a construction event includes the following features:

- **Weather (14):** A vector representing temperature and humidity; and 12 indicators to represent special weather events rain (light, moderate, and heavy), snow (light, moderate, and heavy) severe_cold, severe_storm, severe_fog, moderate_fog, hail, and precipitation_other. Weather data is obtained from [11].

- **POI (15):** A vector of size 15 to represent frequency of POIs (or map annotations) within $r$. Examples of POIs are amenity, crossing, and railway. A full list of POIs can be found in [12] (see Table 2).

- **Road type (25):** A one-hot vector of size 25 to show the type of the road, extracted from [13].

- **Road information (5):** On a road segment with a reported construction, this category offers five attributes, namely road segment distance, average speed, approximate travel time, an indicate to show whether the traffic on road segment was impacted during the construction, and severity of the construction. The latter is an integer value between 1 and 4, where 1 indicates the least impact (i.e., the shortest delay).

To build the aggregated view for all the construction events that occurred during $t$ within region $r$, we simply average over the 59 attributes described above.

### 5.2 Map Image Representation

The road network represented in the map tiles is a relevant spatial context for constructions. Constructions could be less prevalent on a road located in a remote area (with a sparse road network), and more prevalent on a road in an urban area (with a dense road network). Figure 2 shows an example of the type of map images we use, again collected from OpenStreetMap [13]. We represent each zone with one map image at a zoom level of 14 that covers an area of size $5.95km^2$.

![Figure 2: Example of a map image extracted from OSM to (roughly) represent a hexagon zone (zoom_level = 14)](image)

### 5.3 The Deep Road Construction Prediction (DRCP) Model

This section briefly describes our Deep Road Construction Prediction (DRCP) model. The model comprises three major components described below.

- **CNN component:** The use of this component is to encode map image data to extract latent spatial features. It comprises four sub-components, three convolutional blocks (with 4, 32, and 8 channels, respectively) and one decoder component. The decoder component contains six decoder blocks, which are layers with 8 channels in the first and 16 channels in the last three blocks. All decoder blocks include batch normalization to deal with internal covariate shift, max pooling for downsampling, and ReLU. The other sub-components (i.e., three convolutional blocks) do not leverage max-pooling, but batch normalization is used in two of them. The output of the CNN component is then converted to a vector of size 128 by using a flatten layer. Note that the activation function used in the last sub-component is sigmoid to properly concatenate the outputs of CNN and RNN components. The kernel size in all convolutional layers is $3 \times 3$, and stride size is 1.

- **RNN component:** To encode sequential data, we use two layers of Long Short Term Memory (LSTM) with 59 and 45 neurons, respectively. Both layers use sigmoid as activation function. The choice of 59 neurons in the first LSTM layer is to utilize sequential input of size $10 \times 59$ that represents aggregated construction event data over the past 10 time intervals. The output of this component is then converted to a vector of size 40 by using a dense layer with sigmoid as its activation function.
6 EXPERIMENT AND RESULTS
This section first describes experiment setup, followed by results.8

6.1 Experiment Setup
We trained and validated our DRCP model on nine cities (Columbus (OH), New York City (NY), Pittsburgh (PA), Atlanta (GA), Houston (TX), Denver (CO), Miami (FL), Seattle (WA), and Detroit (MI)). The choice of these cities was primarily to achieve diversity in traffic and weather conditions, population, population density, and urban characteristics (road-network, prevalence of urban versus highway roads, etc.). We split our data set into train set (Feb 2016 to Dec 2019), validation set (Jan 2020 to May 2020), and test set (June 2020 to Dec 2020). Each record of data includes aggregated feature vector representation for a 15 days time interval, as well as a map image to represent the corresponding geographical zone. To mitigate label imbalance, we use class weights to better train different models. We empirically (and using the validation set) found weights 1.01 and 16.01 for classes 0 and 1, respectively. As of baseline models, we chose Logistic Regression (LR), Random Forest (RF) with 10 estimators, Gradient Boosting Classifier (GB) with 10 estimators, and a Multi-layer Perceptron (MLP) model with 100 neurons in its hidden layer. We vectorized our data to be used as input for the baseline models.

6.2 Results
Table 2 summarizes experiment results by comparing different models based on F1-score. Based on the results, our proposed model (i.e., DRCP) outperforms baselines with significant margin for 8 out of 9 cities. On average, we observe 2.8% improvement in F1-score when compared to the best baseline for each city. This demonstrates the effectiveness of our proposal to make better use of spatiotemporal information to make future predictions.

Table 2: Comparing different models for selected cities for Scenario I using “F1-score”

| City            | LR  | RF  | GB  | MLP | DRCP |
|-----------------|-----|-----|-----|-----|------|
| Atlanta (GA)    | 0.773 | 0.751 | 0.731 | 0.725 | 0.793 |
| Columbus (OH)   | 0.859 | 0.87  | 0.855 | 0.891 | 0.902 |
| Denver (CO)     | 0.756 | 0.767 | 0.753 | 0.761 | 0.794 |
| Detroit (MI)    | 0.774 | 0.786 | 0.743 | 0.728 | 0.795 |
| Houston (TX)    | 0.891 | 0.895 | 0.892 | 0.884 | 0.908 |
| Miami (FL)      | 0.856 | 0.843 | 0.845 | 0.868 | 0.845 |
| New York City (NY)| 0.895 | 0.898 | 0.884 | 0.906 | 0.942 |
| Pittsburgh (PA) | 0.798 | 0.794 | 0.782 | 0.768 | 0.832 |
| Seattle (WA)    | 0.852 | 0.825 | 0.803 | 0.794 | 0.853 |

7 CONCLUSION
In this paper we tackle the problem of future constructions prediction using heterogeneous spatiotemporal information such as past constructions, weather data, and geographical map data. To our knowledge, this is a relatively new problem space that has not been explored by the research community, maybe due to lack of comprehensive historical data about past constructions. To address this gap, this paper introduces a novel dataset of 6.2 million constructions in the US between 2016 and 2021, that offers a variety of details around location, time, weather condition, map, and road-network. Additionally, we formulate and solve the problem of predicting the possibility of future constructions using such data. We present a deep-neural-network-based model to efficiently utilize the heterogeneous input by combining convolutional and recurrent components in a reasonable setting. Through extensive experiments over multiple major cities in the US, we show the usefulness of our proposal in a real-world setting and in comparison to baselines.

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8All codes and sample input data are available at https://github.com/7Amin/DRCP