Leveraging Data Driven Approaches to Quantify the Impact of Construction Projects on Urban Quality of Life

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ABSTRACT

According to the World Bank, more than half of the world’s population now lives in cities, creating more burdens on the degraded city infrastructures and driving up the demand for new ones. Construction sites are abundant in already dense cities and have unavoidable impacts on surrounding environments and residents. However, such impacts were rarely quantified and made available to construction teams and local agencies to inform their planning decisions. A challenge in achieving this was the lack of availability of data that can provide insights about how urban residents respond to changes in their environment due to construction projects. Wider availability of data from city agencies nowadays provides opportunities for having such analysis possible. This paper provides the details of a generic data-driven approach that enables the analysis of impact of construction projects on quality of life in urban settings through the quantification of change on widely accepted quality of life indicators (e.g., noise, air quality, traffic) in cities. This paper also provides the details of the evaluation of the approach using data from publicly available construction projects information and open city data-portals in New York City. Historical 311 Service Requests from New York City along with twenty-seven road reconstruction projects were used as testbeds in the evaluation. The results showed that 61\% of the projects analyzed in this testbed experienced higher 311 requests after the commencement of construction, with main

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complaints of ‘noise’, ‘air quality’, and ‘sewer’ at the beginning of construction, and ‘sanitation’ and ‘waste’ towards the end of construction. Prediction models, built using regression machine learning algorithms, achieved an R-Squared value of 0.67. The approach is capable of providing insights for government agencies and construction companies to take proactive actions based on expected complaint types through different phases of construction, and avoiding negative influences on the quality of life of urban residents ahead of time.

1. INTRODUCTION

Construction sites are common scenes in already dense cities. In NYC alone, on average, 20 permits per day were issued for new construction projects in 2016 (DOB 2016). Construction projects have indisputable impacts on various aspects of city life, such as environmental effect (i.e., noise pollution, air pollution, and construction waste), public safety (i.e., fatality of general public, emergency response time), and traffic (i.e., traffic delays, lane closing). Previous research studies that looked at the impact of construction on public mostly analyzed one specific area of interest (i.e., noise, air quality, and public safety), instead of providing a holistic view of construction projects’ impact on nearby residents (Butera et al. 2015; Hammad et al. 2016; Kumar et al. 2015). To holistically understand the influence of construction projects on nearby residents, one could evaluate the change in the Quality of Life (QoL) indicators of people by looking at periods before and during construction projects. QoL is defined as the measurement of satisfaction and happiness in life with respect to where we live (Days 1987). Currently, due to the lack of understanding of construction projects’ impact on QoL, government agencies and construction companies could only react to the complaints reported from residents living nearby construction sites, instead of proactively preventing the negative influences that are expected to occur (Zou and Ergan 2018, Zou et. al., 2018). This paper aims to predict how much and what type of negative
influences will occur in a region at different times due to a new construction project through a data-driven approach. This approach can be used by the construction companies and/or government agencies in the planning phase of construction projects to actively predict the impact of construction projects on the quality of life of surrounding residents.

Improving urban QoL has been one of the main goals for policy makers, urban researchers, and city residents. Governments and International Organization of Standardization (ISO) have developed indicators for measuring QoL, monitoring residents’ satisfaction of life, and benchmarking performance of cities around the globe. QoL indicators are separated into two categories as, subjective indicators (e.g., self-perceived health condition, self-perceived happiness level), which measure satisfaction of life at individual levels; and objective indicators (e.g., physical environment, public safety, education), which measure the environmental and societal aspects of QoL (Seik 2000). In the current practice, QoL indicators have been studied via public surveys issued by Census Bureau, researchers, or local agencies aiming at collecting data only for certain indicators such as income and education levels (US Census Bureau 2016, NYC CBC 2017), making it difficult for getting a holistic understanding of QoL of citizens. With the wider availability of open city data and machine learning techniques in recent years, an increasing number of researchers and practitioners started to use open city data as social databases to examine urban problems regarding residents’ QoL (Barbosa et al. 2014). This open data plus machine learning methodologies have already proven to be valuable in various empirical implementations such as predicting air quality levels and crime rates (Liu et al. 2015; Zhan et al. 2017), making sense of taxi data for understanding traffic conditions (Ferreira et al. 2013; Smith et al. 2017; Zou and Sha 2018), and monitoring urban noise problems (Segura-Garcia et al. 2015).
Although data driven methodologies in urban settings have been implemented to solve a variety of urban problems, little effort has been put into understanding the impact of construction projects on QoL in urban settings using open city data. The challenge of doing so is two-folded. The first challenge is the lack of data regarding construction projects. Construction companies hold their historical data (i.e., project estimate, schedules, and bidding contracts) as confidential and use it for competitive advantage in markets (Egbu 2004). However, nowadays in public projects, generic construction data (e.g., project start/end times, milestones, total bid price, etc.) is given public access. Another challenge is the lack of knowledge on how construction related issues map to the QoL indicators. Construction activities affect a wide variety of quality of life indicators (i.e., noise, air quality, public safety), but the relationship between specific construction phases and its impact on quality of life indicators is still unclear.

The objective of this paper is to provide a new quantitative understanding of the impact of construction projects on urban QoL through a data-driven approach, and to predict how much and what type of an impact a new construction project, with similar characteristics (e.g., location, project type) to the previously analyzed ones, would have on QoL. The purpose is to inform construction planners and city officials about proactive measures for minimizing impacts. The approach builds on the mapping of factors identified in the extensive construction literature to the QoL indicators, and is composed of two steps, as: (1) filtering and feature selection in available datasets, and (2) development of machine learning models to “learn” from the past construction projects and predict the impact of a new project on QoL. For implementation and evaluation of the approach, road reconstruction projects in New York City were selected as testbeds, as horizontal projects (e.g., road construction) have a wider footprint to impact existing infrastructure and residents. Open datasets used in the evaluation of the approach include 311 service requests.
(which document non-emergency municipal service requests) and Department of Design and Construction (DDC) construction projects database. For this specific implementation, the prediction models aimed to predict the number of complaints received per complaint type, and the complaints ratio, which is defined as the number of complaints per complaint type divided by the total number of complaints received in the analysis period.

This paper contributes to the existing body of knowledge on construction and QoL research in the following ways:

1. Development of a novel data-driven approach to help construction teams quantify construction projects’ impact on urban QoL by leveraging city datasets, which are becoming more and more available.

2. Providing empirical evidence on construction projects’ impact on QoL in urban settings by conducting case studies using data from construction projects in New York City.

2. BACKGROUND AND LITERATURE REVIEW

This study builds on and extends the work on (a) defining construction related factors on Quality of Life, and (b) standardization efforts and previous research on defining and using metrics to measure QoL. The point of departure for this research is at the intersection of the research conducted in these two areas, where factors defined as influential on QoL in the construction literature are mapped to the indicators defined in standards/previous research.

2.1. Research Studies on Defining Construction Related Factors on QoL

When the literature in the construction domain is analyzed, it is apparent that research studies focused on analyzing the impact of individual factors on the surrounding (e.g., heavy hauling and impact on traffic), instead of a holistic understanding of how construction sites impact the quality of life of residents (Camagni et al. 2002; Hammad et al. 2016; Ivaskova et al. 2015).
Major construction related factors that create public discomfort can be grouped under five categories as noise, air pollution, waste, safety issues, and traffic issues.

Construction noise is one of the main contributors of urban acoustic pollution, affecting citizens’ health and comfort (Ballesteros et al. 2010). Construction noise causes psychological (e.g., annoyance, stress) and physical (e.g., hearing loss, cardiovascular deceases) discomfort of people enduring it (Hammad et al. 2016; Lee et al. 2015). Agencies require monitoring noise at construction sites and keep the noise below certain decibels (e.g., for the use of vibrating pile driver, the limit is 101 dB in NYC) (NYC Environmental Protection 2007). Some governments even allow citizens suffering from heavy noise pollution near construction sites to seek temporary lodging away from the construction projects on the construction companies’ expense (Hammer et al. 2014). Aside from the government regulations, researchers have made strides in construction noise monitoring and mitigation with the goal of helping construction companies to avoid shutdowns and reduce cost (Zou et al. 2007). Construction noise monitoring focuses on the placement of acoustic sensors and accurate recording of the decibel level of the heavy construction machine and overall construction sites (Shen et al. 2005). On the other hand, construction noise minimization includes two distinct directions of research, site layout optimization and construction schedule optimization. Site layout optimization aims to place site material, machinery and temporary structures strategically to occlude noise. Schedule optimization tries to minimize construction noise by separating noisy operations on construction sites to avoid combined acoustic pollution caused by multiple construction activities (Hammad et al. 2016).

Atmospheric emission is another key polluting factor that is associated with construction activities. Environmental audits, which document the energy used and air pollution produced during constructions, show that air emissions (e.g., Fine particulate matter (PM2.5 and PM10) and
$CO_2, SO_2, NO_x$) are byproducts from construction activities and should be monitored (Cole and Rousseau 1992; Kampa and Castanas 2008). Excessive respirable dust generated during construction (e.g., excavation, interior finishing) could also lead to air pollution and eventually health concerns (Lumens and Spee 2001). Previous research on air pollution caused by construction focused on two aspects: air pollution generated during the process of construction material manufacturing (i.e., steel, aluminum, and cement), and the pollution caused during the construction phase (i.e., material transportation) (Chan and Yao 2008; Cole and Rousseau 1992).

Research on finding renewable construction material and clean energy source has created opportunities to reduce air pollution in the process of manufacturing construction material (Cheng and Hu 2010; Cho et al. 2010; Herrmann et al. 1998). During the construction phase, material transportation routes and schedule optimization aim to reduce the cost of transportation as well as the environmental effects caused by heavy hauling (Zhou et al. 2010). Dust control approaches such as reducing on-site manufacturing and proper protection during the demolition process were studied to alleviate the dust issue in construction sites (Tjoe Nij et al. 2003; Wu et al. 2016).

Waste generated during construction projects posts serious problems for construction companies and government agencies for both economic and environmental reasons. Economically, the cost of dumping construction waste has been increasing for the past few decades, causing rising cost for construction companies (Rao et al. 2007). On the other hand, construction and demolition waste being dumped at landfills cause environmental concerns (Poon et al. 2004). Research to address this concern is divided into two parts, including waste management planning in the construction development phase, and recycling/reusing of the demolished construction materials. Simulation studies were often used in the project planning phase to predict construction waste sources and provide optimized site layout and disposal plans to minimize waste generation onsite.
(Wang et al. 2014; Yuan 2013). For recycling construction waste, researchers proposed physical tracking devices for reusable construction parts, and created recycle strategies for construction sites (Li et al. 2005; Shen et al. 2004).

Public safety is another crucial aspect of urban life influenced by construction activities. Ireland Health and Safety Authority reported almost one fatality per month from the general public due to construction activities (Suraji et al. 2001). However, research efforts on construction safety studies mostly focus on construction worker safety and safety regulations (Elbeltagi et al. 2004; Tam et al. 2002, 2004). Construction impact on public safety is mainly studied in projects where interactions with public is unavoidable such as airport reconstruction and hospital renovation projects (Toor and Ogunlana 2010). The available studies are also case examinations that reflect on immediate tragedies of public fatalities caused by construction activities (Müngen and Gürcanli 2005; Wang et al. 2008). One of the reasons for the lack of research in the public safety domain is the lack of data. While agencies such as Occupational Safety and Health Administration (OSHA) keeps track of work fatalities, the raw data for analyzing construction caused public safety problem is limited.

Infrastructure construction projects also cause traffic delays because of the extended construction sites and road closures. Previous research on minimizing the traffic influences caused by construction activities considers the traffic slowdown as part of the construction cost, and then apply optimization methods to reduce the overall cost as much as possible (Lee 2009). Another factor being considered for construction affected traffic situation is the construction schedule. Optimization methods have been applied to shorten the construction duration, hence reducing the total amount of time wasted due to construction projects (Carr 2000; Lee et al. 2005; Yepes et al. 2015).
Abundant evidence has proved undeniable impacts of construction on various aspects of Quality of Life (QoL) of nearby residents. However, little research has been done to inspect construction projects’ impact and quantify the impact of construction projects using QoL indicators.

2.2. Standardization Efforts and Previous Research on Defining and Using Metrics to Measure QoL

The efforts under this subtitle fall into two categories as studies/efforts to define metrics to quantify QoL systematically, and studies that used such metrics for quantifying aspects of QoL in selected regions. Researchers as well as standardization organizations have been working on defining indicators of QoL. A landmark study in early 2000s included 18 QoL categories as: social life, working life (career), family life, education, wealth, health, religion, leisure, self-development, housing, media, politics, consumer goods, public utilities, transportation, health care, environment, and public safety (Seik 2000). Later survey studies often followed similar design paradigms for the survey categories (Das 2008; McMahon 2002; Santos and Martins 2007). The objective of these survey studies was to define a comprehensive list of subjective indicators of QoL and establish a mature QoL surveying and analyzing system, which could be used in future studies for consistent monitoring and comparison of citizens’ subjective responses on QoL.

When the efforts from standardization bodies are analyzed, we see that they aim to define metrics that are quantifiable. These metrics are objective indicators of QOL mainly covered in the International Organization of Standardization (ISO) Sustainable Develop of Communities – indicators for city services and quality of life. There are seventeen city performance categories (i.e., objective indicators) defined for comparing performances of cities, including economy, education, energy, environment, finance, fire and emergency response, governance, health,
recreation, safety, shelter, solid waste, telecommunication and innovation, transportation, urban planning, waste water, and water and sanitation (ISO 2014).

In recent years, the popularity of big data and machine learning techniques sparked new methodologies for objectively measuring QoL (Ferreira et al. 2013; Liu et al. 2015). Various objective QoL indicators (e.g., transportation, public health, and economics) were studied using vast amount of data collected privately or publicly (Du et al. 2017; Du et al. 2018; Ferris et al. 2010; Kasireddy et al. 2016; Ruths and Pfeffer 2014; Zheng et al. 2013). In the area of transportation, taxi trips data in New York City has been analyzed using spatio-temporal algorithms to gain insights on taxi ridership and social events in the city (Doraiswamy et al. 2014; Ferreira et al. 2013; Phithakkitnukoon et al. 2010). For public health, researchers provided prediction tools for the spread of diseases by combining various data sources (e.g., Google searches, Tweets and hospital visiting records) (Lee et al. 2010; Santillana et al. 2015; Zou and Ergan 2019). For economics, administrative data from agencies such as Internal Revenue Service and Center of Medicare and Medicaid have been used to predict economic behavior (Bose and Mahapatra 2001; Einav and Levin 2014). However, no studies focused on construction projects’ impact on urban QoL indicators. This paper fills the gap of quantitative construction impact study on QoL in urban settings. In addition, as a result of the review of two domains defining factors and indicators, the authors could be able to map the construction related factors to QoL indicators, as shown in Figure 1. This mapping will be used as a given when building prediction models using the approach.
This paper proposes a data-driven approach for quantification, prediction, and interpretation of impact of construction projects on urban QoL. In a nutshell, the proposed approach has two main steps. The first step includes pre-processing of datasets with (a) filtering the construction projects and open city datasets to create a subset of data for a selected analysis period, and (b) feature selection to eliminate the non-essential fields in datasets that are not statistically significant to the final prediction targets. The next step includes building prediction models using the selected subset of features from the filtered datasets. Regression models are suggested here since the objective of the study is to quantitatively predict the impact of construction projects on urban QoL, and such impacts could be defined mathematically as measurements of QoL (e.g., number of 311 complaints from residents about construction). Finally, the best performing models are used to predict the impacts in new construction projects. The steps are further explained in detail in the following sections.

Figure 1. Mapping between Construction Related Factors and QoL Indicators.
3.1. Step 1. Data Pre-Processing: Filtering and Feature Selection

In the pre-processing process, construction projects in the available project database should be filtered to create the needed subset (e.g., road construction). Filters such as the construction type (e.g., new building construction, road construction), construction location (e.g., dense cities, suburbs), construction commencement date, and construction duration should be defined ahead of time based on the characteristics of the new construction project for which the impact analysis will be performed (Figure 2 first box). Open city data should be filtered so that it only contains information related to the area of interest for the data analysis. For example, one can define the analysis period for construction projects to be two years (i.e., one year before the start date of projects and one year after their start dates), and data that is beyond this analysis period should be deleted. Aside from filtering, feature selection on open city datasets is also needed. Feature selection can be done using various data-driven algorithms, such as filter, wrapper and embedded methods. The feature selection process can filter out the fields in open city data that do not play an essential role for the final prediction target. In general, this step is shown in Figure 2 (second box) with illustrative examples.
Feature selection of the open city data is crucial, since poorly selected features could affect the accuracy of prediction models (Dash and Liu 1997). The significance level of each open city data field (e.g., complaint types in 311 data) from the selected data sources should be examined. Only the significant features/fields need to be retained for further to fit prediction models. Plenty of algorithms could be used for feature selection. In general, feature selection algorithms could be divided into three groups, filter, wrapper, and embedded methods (Jain and Zongker 1997). As the name suggests, filter methods test each feature’s significance level to a model containing that feature, and eliminate it if the feature is not found to be statistically significant in the final prediction model. Different criteria could be used for the calculation of significance level, such as t-test and log-likelihood ratio test. Wrapper and embedded methods do not directly apply statistical tests on the features. However, they select the most suitable features by comparing the data analysis model performance by examining all subset configurations of the features. Wrapper methods select the most essential features by eliminating (i.e., Backward Selection) or adding (i.e., Forward Selection) features to the existing set of features, and create data analysis models with each set of features. Features that return the best performing model are selected as the final feature set. Embedded methods are similar to the wrapper methods with one major difference that the embedded methods also have feature selection capabilities, and in each iteration of subset feature selection, the embedded methods perform feature selection simultaneously. At last, the best performing method is seen to have the most influential features, and those features are retained. Although the wrapper and embedded methods are time consuming to implement, they could exhaustively test all configurations of the features (Dash and Liu 1997). As a result, in this study, an embedded method (i.e., Decision Tree) was used to conduct the feature selection during the implementation phase.
3.2. Step 2. Building Prediction Models and Performing Cross-Validation

For this step, prediction models are built using various machine learning models. The input for this step is the pre-processed datasets. The specific machine learning algorithm selection depends on the purpose of the study. If the objective is to predict an exact number or class of a QoL indicator, supervised regression or classification methods are needed. On the other hand, if the objective is to explore clustering behavior of certain QoL indicators, unsupervised clustering techniques should be applied. An overview of this step with illustrative examples is provided in Figure 3.

Figure 3. IDEF0 Diagram Showing the Building Prediction Models and Cross-Validation.

For this study, the objective is to predict the impact of construction projects on urban QoL. As will be discussed later in the paper, the impact is measured by numerical values. Such metrics are best captured with regression models, hence regression methods are suggested in this approach to build the prediction models (Figure 3 first box). Specifically, Ordinary Least Squares (OLS), Random Forest (RF) with Adaboost, and Decision Tree (DT) were implemented in the evaluation of the approach. The reason to include multiple methods is to evaluate model performances and
suggest the best performing one for predicting impact of construction projects on urban QoL indicators. OLS is suggested for implementation as it is one of the simplest ways of implementing linear regression (Craven and Islam 2011), and is commonly used as a benchmarking model for other machine learning methods to compare to. Since the assumption of linearity in linear regression is almost certainly too aggressive for urban data, linear regression was expected to produce the least accurate result for this problem. Ordinary Least Squares (OLS) Regression takes the following mathematical form, represented in Equation 1:

$$ y_{ij} = \alpha + \beta x_{ij} + \epsilon_{ij} \quad (1) $$

Where $i \in (1, \ldots, N)$ represents distinct observations (i.e., one row in data), and $j \in (1, \ldots, M)$ represents different features in the data. $y_{ij}$ is the dependent variable, or target variable. $\alpha$ in equation (1) represents the intercept of the model, and $\beta$ is the vector of estimated coefficients. The main assumption for OLS regression is that the error term $\epsilon_{ij}$ is assumed to be an independent, identically distributed (IID) random variable. The least squares could be achieved when minimizing the error term $\epsilon_{ij}$.

RF with Adaboost is also suggested in this approach because of its unparalleled accuracy as a regression model, and its capability of being used without the need for extensively large datasets or long training times. Earlier studies that compared ten most widely used supervised learning techniques on empirical datasets showed that Random Forest algorithm being the second-best performer, only after Boosted Trees with tuned parameters (Caruana and Niculescu-Mizil 2006). RF is one of the ensemble algorithms, which creates a “bag” of base models, and use the aggregation of base models as the final result. Adaboost is also implemented in the RF algorithm. Adaboost creates multiple base models in order, and improve its own performance based on the
previous model’s errors. In the RF algorithm, the base model is often selected as the regular Decision Tree (DT) Regression. As a result, this paper included the DT algorithm as a comparison to examine if the addition of boosting created any improvement on the prediction model. The DT algorithm is created based on a Tree Structure. Branches in regression trees are carrying weights that represent the confidence level of the choices made by the branches. The final regression value is a weighted aggregated value from all leaf nodes.

As a last step, for each algorithm used in the process for fitting models, cross validation is implemented for getting the best fit out of the models (Figure 3 first box). Cross validation randomly separates the data into training and validating parts based on a predefined training/testing ratio. Each regression algorithm builds the prediction model based on the training data, and tests the performance of the model using validation data. After a user-defined number of iterations, the best performing model is selected from the validation results.

The best performing prediction model can be selected using a series of criteria, such as bias, variance, R-Squared value, and mean squared error (MSE), as shown in Figure 3 (second box). While bias and variance are commonly used for a variety of statistical purposes, R-Squared and mean squared error (MSE) are usually used with the purpose of measuring the goodness-of-fit for models. R-Squared value is commonly regarded as the first choice of benchmarking parameter to use (Salakhutdinov et al. 2007). Models with high R-Squared value have higher probability of correctly predicting unseen data. Bias and variance could be calculated for models with different model parameters, with the goal of finding a low bias and low variance model. Low bias means less sum of error for the prediction model, whereas low variance means high confidence of the predicted value falls near the mean of true values. When bias and variance move on different directions with the change of model parameters, MSE could be used to moderate between model
bias and model variance. Because MSE is calculated as the sum of squared bias and variance (Salakhutdinov et al. 2007), minimizing MSE could lead to a balance point where the model produces both low bias and variance.

Once the final prediction model is selected based on the model performances, predictions on new construction projects can be performed. For regression models used in this study, the output (i.e., prediction target) is a vector of continuous float generated for rows of new input data. Finally, the prediction result could be interpreted for future proactive actions.

4. EVALUATION OF THE APPROACH

4.1. Overview of the Datasets Used for Evaluation

This paper used open city data to measure construction projects’ impact on urban QoL. The construction data was collected from the online project repository from New York City Department of Design and Construction (NYC DDC 2018). To measure the construction projects’ impact, 311 Service Requests data was used as open city data. As it will be shown in the following sections, 311 data could serve as a bridge to map urban QoL indicators to construction projects, since numeros types of 311 Service Requests show statistically significant differences for before and during construction times. The 311 Service Requests data was collected from New York City’s online open data portal (DoITT 2018).

Construction Projects in Manhattan

The New York City Department of Design and Construction (NYC DDC) serves as the project manager for the city’s capital projects. NYC DDC’s portfolio includes a wide variety of construction projects, such as horizontal projects (i.e., roads, bridges), vertical projects (i.e., buildings, towers), and renovation projects. In this study, construction projects containing road reconstruction were selected as testbeds due to their larger impact zones. Road reconstruction
projects have the potential to affect many residents’ QoL due to the extended construction sites, heavy machinery involved, and road closures, while the scale of influence of vertical construction projects is often limited to the construction block. The larger influence area provides a larger pool of impacted residents.

**311 Service Requests from 2010 to Present**

The open city data used in this study is 311 Service Requests from 2010 to present. The latest access date of this data is 01/31/2018. 311 service requests are collected through 311 calls, which document non-emergency complaints from NYC residents. The data is published publically on NYC open data portal, and is updated daily. The dataset could be downloaded in CSV format, with 53 columns and more than 16 million rows, containing 311 requests from five boroughs of NYC since 2010, with 175 different types of complaints. The downloaded CSV file was about 11 Gigabytes in size, providing detailed information about each 311 request.

**4.2. Implementation and Results**

This section provides the details of the implementation and evaluation of the approach using specific datasets, i.e., DDC construction data and 311 service requests calls. The implementation results are discussed for each step of the approach in the following subsections.

**Data Pre-Processing and Feature Selection for 311 Service Requests and DDC Construction Projects DataSets**

In order to create a precise prediction model for a certain type of construction project (i.e., road reconstruction projects), a series of constraints were applied to the NYC DDC project pool to select a subset of projects. Firstly, the location of analysis was set to the borough of Manhattan, due to its large population and constant ongoing road construction. Roosevelt Island was taken out of the analysis, because it sits on the East River, away from Manhattan, and is a self-contained,
enclosed environment. Secondly, the analysis period of each construction project was set to two years, (i.e., one year before the construction, using as baseline, and one year after the construction commencement). Finally, the total construction duration of selected projects was set to be longer than one year, because short construction projects may not have triggered changes of residents’ QoL due to the short time for reaction. After applying these constraints, 27 projects were left at hand from the NYC DDC pool of 428 projects in total. Projects used in the analysis is summarized in Table 1.

Table 1. Summary of the Construction Projects Included in the Analysis.

| #  | Start      | Duration            | Zip  | #  | Start      | Duration            | Zip  |
|----|------------|---------------------|------|----|------------|---------------------|------|
| 1  | 08/05/13   | 4 years             | 10004| 15 | 01/31/17   | 2 years 6 months    | 10002|
| 2  | 09/23/13   | 1 year 9 months     | 10034| 16 | 10/27/14   | 2 years             | 10014|
| 3  | 04/14/14   | 2 years 2 months    | 10016| 17 | 07/06/15   | 2 years             | 10012|
| 4  | 04/15/14   | 2 years 6 months    | 10035| 18 | 06/29/15   | 1 year              | 10065|
| 5  | 07/22/14   | 1 year 4 months     | 10030| 19 | 05/15/16   | 1 year              | 10028|
| 6  | 11/24/14   | 1 year 7 months     | 10028| 20 | 01/20/14   | 1 year 6 months     | 10032|
| 7  | 12/31/14   | 2 years             | 10014| 21 | 06/30/15   | 1 year              | 10039|
| 8  | 06/29/15   | 1 year              | 10021| 22 | 06/01/16   | 2 years             | 10013|
| 9  | 01/04/16   | 3 years             | 10001| 23 | 01/06/15   | 1 year 6 months     | 10040|
| 10 | 02/15/16   | 5 years             | 10007| 24 | 08/05/13   | 3 years             | 10003|
| 11 | 03/07/16   | 1 year              | 10128| 25 | 09/16/13   | 2 years             | 10007|
| 12 | 05/31/16   | 1 year 1 months     | 10033| 26 | 10/20/16   | 2 years             | 10016|
| 13 | 06/01/16   | 2 years             | 10031| 27 | 03/01/17   | 1 year 6 months     | 10007|
| 14 | 06/27/16   | 2 years 6 months    | 10038|    |            |                     |      |

The open city data used to measure in this study is 311 Service Requests from 2010 to Present. The original file downloaded in CSV format is about 11 Gigabytes, which would demand excessive computing time for data analysis. Therefore, data pre-processing (e.g., filtering and feature selection) was crucial. The data provides repetitive information regarding each complaint, such as Intersection and Cross Streets. As a result, before applying feature selection, the columns that include repetitive information was deleted to only retain the essential information about the complaints. In the filtering phase, any data with a time-stamp earlier than one year before the
earliest start time of the analyzed construction projects was removed from the dataset because the data falls out of the data analysis period. After applying these filters, the total file size was about 4 Gigabytes, which is much more manageable for the data analysis. A snippet from the service requests dataset is provided in Table 2.

| Unique Key | Created Date | Agency | Complaint Type | Descriptor | Incident Zip | Borough |
|------------|--------------|--------|----------------|------------|--------------|---------|
| 36154062   | 5/11/17 09:18 | DOB    | General construction | Construction | 10002    | Manhattan |
| 36154109   | 5/10/17 15:49 | DOT    | Street condition | Construction congestion | 10075    | Manhattan |

For the 27 projects selected in this study, 26 were used as training and validating projects, and the 27th was randomly selected, and used as an unseen project for testing the performance of prediction models. In order to create 26 training and validation datasets from the 311 service request data, for each project, the construction influence zone was set to the zip code of the project, and the data analysis period was set to two years (i.e., one year before the construction, and one year during the construction). Each type of complaint recorded during the analysis period was grouped monthly using the following formula to avoid high scarcity of the data, because some types of complaints do not occur daily or weekly.

\[ C_t^i = \sum_{n=1}^{N} count(i) \]  \hspace{1cm} (2)

In Equation 2, \( C_t^i \) is the aggregated count for a given complaint type, \( i \), for time \( t \), where \( i \in \{1,2, ..., 175\} \), and each \( i \) represents one type of complaint; \( t \in \{1, 2, ..., 24\} \), represents the month and year for the complaint, \( n \in \{1,2, ..., N\} \) represents the day of month, and \( N \) is the total number of days in month \( t \). The aggregated results \( C_t^i \) could be seen as a total of 175 distinct complaint types, 24-row (i.e., 12 months before construction and 12 months during construction)
and 55 column data chunks (with an aggregated count of each complaint type and complaint ratio calculated as the last two columns). The aggregated count and complaints ratio were used as the target variables for the prediction models.

To further select the columns in the 311 service request data that are capable of generating accurate prediction models for the target variables, we implemented an embedded feature selection method, Decision Trees (DTs). The reason of using DTs as the feature selection method is that (1) embedded method could exhaustively test all subsets of features, and (2) DTs would also be used in the prediction model step, and having the same method in feature selection step could create a subset of features that are best suited for the prediction. In Decision Trees, the level of a node in DTs is decided by the weight that node carries. As shown in Figure 4, complaint type has the highest weight (root node), while incident zip code and created date (level one) having the second and third highest weights. Due to the space constraints, only part of the DT is shown in Figure 4.

![Figure 4. Embedded Feature Selection using Decision Tree.](image)

Large open city datasets, such as 311 service requests, could contain categorical data within one data field (i.e., one column of the dataset). In order to determine the categories that are statistically different between before and after the construction starts, statistical methods can be used to determine the significance level of each category in a given field. Out of all 175 different
types of complaints (hence categories) possible to record in the 311 dataset, only a subset were influenced by construction activities. To determine the complaint types that are closely related to the construction projects selected, t-test was used on every type of complaint happened during the two-year analysis period. P-values were calculated for each type of complaint to identify the complaint types that significantly changed with respect to before and after a construction project starts. If the p-value is less than 0.05 (i.e., there is a 95% confidence level that the distribution of one type of complaint was different between before and during the construction), the complaint type was seen as statistically significant and was included in the analysis. Furthermore, to ensure the complaint type was not associated with only a small number of construction projects, only complaint types that occurred more than five times in all 26 training projects were used to build the prediction models. It should be noted that the complaint types determined by the significance test are then filtered based on Table 1 mapping of construction factors to QoL indicators. Complaints that passed the t-test but were not part of Table 1 were excluded from the analysis. A final list of complaint types selected in this study is shown in Table 3. As seen in Table 3, a total of 15 types of complaints were selected.

**Prediction Models Built**

First, two prediction target variables were defined to serve as labels for the training and validation datasets as: the aggregated number of requests received for each type of complaint in each month (i.e., complaint count defined as $C_t^i$ in Equation 1), and the complaint ratio, which represents the number of complaints per complaint type divided by total number of complaints received, as shown in the following formula, where $C_t^i$ is the target variable defined in Equation 1.

$$Y_t^i = \log \left( \frac{C_t^i}{\sum_{l=1}^{i} C_t^l} \right)$$

(3)
The reason of using $Y_t^l$ (i.e., complaint ratio) as a target variable is to measure importance of a certain type of complaint among all complaint types. The logarithm is used to generate a smooth series of value, in case that the change of complaint ratio is too large.

Table 3. Selected of Complaint Types in 311 Dataset for Building Prediction Models and Corresponding QoL Indicators

| QoL Indicator | Complaint Types                                      | Frequency |
|---------------|------------------------------------------------------|-----------|
| Environment   | Noise                                                | 5         |
|               | Noise construction                                   | 5         |
|               | Air quality                                          | 5         |
|               | Water system, hot/cold water systems, plumbing       | 6,7,5     |
|               | Street condition                                     | 11        |
| Waste         | Solid Waste                                          | 7         |
|               | Waste Water(Sewer)                                   | 5         |
| Safety        | Project inspection                                   | 6         |
|               | Safety                                               | 6         |
| Transportation| Parking                                              | 7         |
|               | Metering                                             | 8         |
| Other         | Building use                                         | 7         |
|               | General construction                                 | 8         |

The prediction models were then created to best fit the training data, and generate most accurate prediction results on two target variables for new construction projects. First, parameter tuning was done to generate the best performing model using three regression algorithms (i.e., Ordinary Least Squares, Random Forest with Adaboost and Decision Trees). For OLS method, there exists one optimal solution when using Maximum Likelihood algorithm. The result of OLS was used as a baseline comparison with DT and RF with Adaboost. As for RF and DT algorithms, parameter tuning was done by minimizing the MSE value and maximizing the R-Squared value. For the accuracy of the models, each algorithm was executed 1,000 times to get average MSE values and R-Squared values.

Two parameters in RF algorithm determine the accuracy of the prediction model created, namely, depth of tree (i.e., the maximum depth of the base model decision trees) and number of
estimators (i.e., the number of different base models created). The authors tested both parameters in the range of 1 to 20. Note that, to create a consistent comparison among various configurations of depth of tree and number of estimators, the training data was normalized to the scale of 0 to 1.

The result of RF algorithm with Adaboost for the first target variable (i.e., complaint count $C^i_t$) is shown in Figure 5. Figure (5a) shows the R-Squared values of different configurations. High R-Squared value is represented with dark red, whereas dark blue represents low R-Squared value. So, the highest R-Squared value and lowest MSE value produced by RF algorithm with Adaboost are highlighted in black squares, when the number of estimators is 12, and depth of tree is 8.

![Figure 5. Results of RF with Adaboost Prediction Model for Number of Complaints/Type.](image)

**Figure 5a (left):** R-squared value with changing configurations of the depth of tree (y-axis) and number of estimators. (x-axis)

**Figure 5b (right):** MSE with changing configurations of the depth of tree (y-axis) and number of estimators (x-axis). Larger value is represented with dark red, and smaller value in dark blue.

Similar to the RF algorithm with Adaboost, regular DT algorithm’s parameter-tuning could also be done by maximizing the R-Squared value and minimizing the MSE. One key difference between DT and RF algorithm with Adaboost, is that DT only has one parameter, depth of tree, as a factor to effect the accuracy. The results of DT algorithm for the first target variable (i.e., complaint count $C^i_t$) are shown in Figure 6. It is easy to find that, when the depth of tree is set to 5
(as circled in Figure 6), the DT algorithm returns the best performing model in terms of R-Squared value and MSE.

![Figure 6](image)

**Figure 6.** Results of Decision Tree Prediction Model for Number of Complaints/Type.
*Figure 6a (left):* R-Squared value (y-axis) with changing configurations of the depth of tree (x-axis).
*Figure 6b (right):* MSE (y-axis) with changing configurations of the depth of tree (x-axis).

Finally, the R-Squared value of each model with tuned parameters, is presented in Table 4. It is seen that the RF algorithm with Adaboost produced the highest R-Squared value among three algorithms. DT algorithm with tuned parameters produced slightly lower R-Squared value than RF algorithm, and the OLS algorithm generated the worst performing predictive model with an R-Squared value of 0.20 because of the over-aggressive assumption of data linearity.

| Algorithm     | OLS | DT | RF with Adaboost |
|---------------|-----|----|-----------------|
| R-Squared Value | 0.20 | 0.62 | 0.65 |

Table 4. R-Squared Value for OLS, DT, and RF with Adaboost.

Just like the first target variable (i.e., # of complaints/complaint type), the second target variable (i.e., complaint ratio) was also predicted using the three regression algorithms. The parameter tuning and final model selection processes were identical to the ones that were used in the first predicted variable. The results of RF algorithm with Adaboost and DT algorithm are shown in Figure 7 and Figure 8. As seen in Figure 7, the highest R-Squared value and lowest MSE value were achieved when the depth of tree was 12 and number of estimators was 11 for the RF
algorithm with Adaboost. For the DT algorithm, as the results in Figure 8 suggest, the DT algorithm achieved the best R-Squared and MSE values when the depth of tree was set to 15.

Figure 7. Results of RF with Adaboost Prediction Model for Complaints Ratio.  
Figure 7a (left): R-squared value with changing configurations of the depth of tree (y-axis) and number of estimators (x-axis).  
Figure 7b (right): MSE with changing configurations of the depth of tree (y-axis) and number of estimators (x-axis). Larger value is represented with dark red, and smaller value in dark blue.

Figure 8. Results of Decision Tree Prediction Model for Complaints Ratio.  
Figure 8a (left): R-Squared (y-axis) value with changing configurations of the depth of tree (x-axis).  
Figure 8b (right): MSE (y-axis) with changing configurations of the depth of tree (x-axis).

The R-Squared values for best performing models of the second target variable, complaint ratio, are shown in Table 5. It is observed that the RF algorithm with Adaboost again produced the highest R-Squared value, meaning that the model created using RF algorithm performs the best when used for predicting construction complaint ratio defined in Equation 3.

Table 5. R-Squared Value for OLS, DT, and RF with Adaboost.

| Algorithm      | OLS | DT | RF with Adaboost |
|----------------|-----|----|------------------|
| R-Squared Value | 0.17 | 0.58 | 0.67 |

**Interpretation of Results**

After the parameter tuning, the individual models created using OLS, DT, and RF are compared for an overall best performing prediction model, by comparing the prediction result of three models using the unseen 27th construction project’s data. The final prediction result is shown below in Figure 9, where the horizontal axis is the true value of the complaint count (Figure 9a) or complaint ratio (Figure 9b), and the vertical axis is the corresponding predicted value. The more accurate the prediction, the closer will be the prediction points to the diagonal 45-degree line. It could be seen that RF algorithm with Adaboost achieved better prediction over the unseen test project for both target variables. Because the predicted points are evenly separated on both sides of the 45-degree line, bias is lower for RF algorithm with Adaboost in both target variable tests. The same logic could be applied to variance, where the predicted points generated by RF algorithm are generally closer to the 45-degree line than the DT model. As a result, RF algorithm with Adaboost produced the best performing models for both target variables. It can also be observed that the complaint ratio is more evenly distributed along the normalized range (i.e., 0-1), because of the introduction of logarithm in the definition of complaint ratio.

![Figure 9. Predicted (y-axis) vs. True value (x-axis) of Target Variables using DT and RF.](image)

*Figure 9a (left) Results for the target variable: # of complaints/complaint type*

*Figure 9b(right): Results for the target variable: complaint ratio*
Further interpretation could be drawn from the predicted results. For example, for # of complaints, in the training dataset, 16 projects out of 26 (i.e., 61%) saw an increase in total number of complaints reported in 311 Service Requests. Additionally, the number of complaints, complaint ratio, and their percent changes will be informative for understanding the impact of each construction project on urban QoL. The predicted results of each type of complaint was examined and provided in Table 6 for the test project.

Table 6. Percentage Change # of Complaints and Complaint Ratio for a Set of Complaint Types

| Complaint Type               | Change in # of Complaint*       | Change in Complaint Ratio*       |
|------------------------------|---------------------------------|----------------------------------|
| Air Quality                  | 71% (month 1-4)*                | 15% (month 1-4)*                 |
| Sewer                        | 23% (month 1-3)                 | 6% (month 1-3)                   |
| Safety                       | 52% (month 4-8)                 | 11% (month 4-8)                  |
| Noise Construction           | 10% (month 1-3)                 | 19% (month 1-3)                  |
| Unsanitary Street Condition  | 7% (month 10-12)                | 3% (month 10-12)                 |

*Information in the parenthesis is showing the time-frame that the change happened for the corresponding complaint type with respect to the start of the construction project (used for testing).

These detailed results show correlations with schedule of activities at the beginning (e.g., excavation, earthwork, underground site condition improvements resulting in air quality, noise and sewer issues around) and the later stage of construction projects (e.g., construction waste such as dust blown out of construction sites, and safety issues caused by heavy machinery) and provide insights for construction companies and government agencies to understand how construction projects are affecting surrounding residents’ QoL in certain periods of construction. In this case, the residents were experiencing dirty street conditions at the end of construction, and extensive noise and low air quality at the beginning of the construction. The increase in the noise and air
quality complaints toward the start of construction could be explained by the heavy machinery used during the excavation period for road reconstruction projects. The increase in sewer related complaints are caused by the excavation, and interrupting the sewerage system when working around/on pipes. The results show that, construction companies could potentially use this information to actively prevent noise pollution at the beginning, inform public about possible issues with water and sewer systems, and put more efforts into cleaning the environment towards the end of construction.

CONCLUSION AND FUTURE WORK

This paper proposed a data driven approach to quantify and predict the impact of construction projects on urban QoL. The approach was implemented on 27 road reconstruction projects managed by NYC DDC in the borough of Manhattan. Three regression algorithms, Ordinary Least Squares, Decision Trees and Random Forest with Adaboost, were used for building prediction models. Two target variables, the complaint count and complaint ratio, were defined for prediction accuracy test. Results show that Random Forest with Adaboost produced the best performing prediction model for both target variables. The prediction results show that the final prediction model achieved R-Squared values of 0.65 and 0.67 on both target variables. Empirical implications of the prediction results were discussed (e.g., air quality, construction noise and sewage related complaints increased as soon as the construction starts; safety and street sanitary related complaints increased in the later part of the construction period). It is shown that the approach could potentially provide insights for construction companies and government agencies to understand how construction projects are affecting surrounding residents’ QoL. Practitioners can use the generic steps provided for this approach to build models using the data available from their localities to quantify the impact of new construction projects on certain QoL indicators.
Future work is needed to improve the current research. This paper only tested the data driven approach using limited construction projects in a specific city as testbeds. Extended studies of the approach on other types of construction projects and cities will be needed. This work will also be extended to include other types of open city data that can complement the 311 dataset, such as emergency response data, through which impact of construction on traffic conditions can better be quantified.

In conclusion, this paper is a first attempt on using open city data and construction related data to quantify and predict the impact of construction projects on urban QoL. This study could serve as a guide for future construction related QoL research, in a sense that it utilized open data and machine learning algorithms instead of traditional survey studies. This paper also provided a fresh angle for looking at the impact of construction projects by integrating open city data sets and data driven approaches.

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