ParkSmart

Park Smart. Worry Less.

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In collaboration with Honda and the city of Columbus, Ohio.

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Abstract

ParkSmart is a machine learning-based parking guidance system that provides users with a way to find nearby street parking, based on a predictive tool that uses historical data to identify locations where parking is likely to be available. ParkSmart provides turn-by-turn directions to the best parking spots around a user's inputted destination and helps drivers save time and money, through advanced statistical methods and data science techniques. Using neural network-based time series and forecast models, ParkSmart is designed to predict which zones of Columbus, Ohio, have the highest levels of open parking based on past vehicle trip logs and historical parking meter data. ParkSmart can predict an available spot with 85% accuracy and can help save Columbus drivers an average of 4.5 minutes on each driving trip, nearly 1.2 kilometers of driving at the end of their trips and prevent about 287 grams of carbon dioxide from being polluted into the atmosphere, per trip. ParkSmart was created by a team of Data Science, Electrical Engineering and Computer Science undergraduates at UC Berkeley and developed in collaboration with Honda and the city of Columbus, Ohio.

Introduction:

Automation and optimization have taken over the transportation industry. From autonomous vehicles to more efficient route guidance systems and from real-time bus updates to the rise of Uber and Lyft, technological solutions are transforming the way we travel. However, one sector that has been slow to adapt to this technological change is the parking industry. While society is starting to see the rise of parking payment applications, it is still very rare to see any sort of parking guidance system that directs drivers to nearby parking spots.

To this day, drivers struggle to find open parking spots, especially in big cities. Parking is an annoyance that nearly every driver experiences. American drivers spend an average of seventeen hours per year, just searching for parking. This results in an average cost of $345 per drivers per year, or $73 billion for all Americans, for drivers just looking to park their car.

This problem also affects the economy from a macroeconomic scale. In an INRIX survey of U.S. drivers, 63% noted that there were times that they avoided driving to a destination due to the difficult nature of finding parking in an area. This dramatically impacts regional businesses and economic activity. Specifically, 39% of respondents avoided going to a shopping destination because of the lack of availability of parking. This certainly reduces the number of people who go out and makes it more difficult for new economic activities. Additionally, it causes Americans to experience higher stress levels. According to that same survey, 61% of Americans drivers report that they feel stressed when trying to find a parking spot, 42% missed an appointment due to lack of parking, 34% abandoned a planned trip due to the unavailability of parking and 23% experienced road rage. This level of anger at parking also has economic impact as people have missed various opportunities of spending money, due to lack of parking.[1]

Not only does this extra time idling and driving around add up monetarily, it also means larger amounts of carbon dioxide emissions, which negatively impacts the environment. If we, as a society, can quell this problem, we can save the planet from millions of kilograms of unnecessary carbon dioxide emissions. This is clearly a multifaceted problem.

The vastness of this problem means that it is certainly one worth attempting to solve. This is why ParkSmart was created. ParkSmart is an machine learning-based parking guidance system that provides users with a way to find nearby street parking. Our solution was created by a team of Data Science and Computer Science undergraduates at UC-Berkeley and developed in

[1] Inrix. “Searching for Parking Costs Americans $73 Billion a Year - INRIX.” *INRIX*, INRIX, 12 July 2017, inrix.com/press-releases/parking-pain-us/.

collaboration with the multinational car corporation Honda and the city of Columbus, Ohio, and their Smart Columbus initiative.

ParkSmart allows users to observe and get directions to the best spots to park their cars, around their destinations. By being able to see the available street parking nearby, users will save time and reduce their parking stress through our suggestions on where they should park. ParkSmart aggregates data from different sources to help users find parking and uses a variety of statistics based on years of past city behavior. Additionally through this, ParkSmart helps benefit the local economy by getting drivers to shops and restaurants quicker. ParkSmart also incorporates past parking data to help drivers avoid areas of high ticketing. It also helps cities ease congestion by reducing driver circling patterns and helps remove cars from the road. Finally, as the ultimate goal is to implement our system in current Honda car dashboards, it should be easy to understand and is cleanly presented for drivers to easily see and drive to areas where there is open parking.

Research:

A parking guidance system is not a novel idea. Academics and researchers have been exploring the concept for nearly fifty years. However, due to the explosion of various forms of reliable information about parking habits as well as the advent of the Digital Age, it is now increasingly possible to create a large-scale, crowd-sourced solution where drivers can easily identify open parking locations. Consequently, there are various companies and technologists who are building tools that help users identify whether a parking spot is open.

Before considering the implications and design of a current solution, we must understand the previous work that has been done on the subject of parking guidance systems.

In their 1991 "*Review of urban car parking models*,**"** Young, Thompson and Taylor analyzed various methods of governmental strategic planning initiatives for how cities manage their car parking inventory. Ultimately, they found that even though parking facilities have a large impact on a city's traffic flow and transport systems, political decisions about these facilities are made on an ad hoc basis and don't consider a holistic view of the network. They also note that current technological solutions for parking management focus on choice, allocation and interaction models. Ultimately, this helps us understand that our solution needs to be done using governmental data, which ParkSmart has done through working with Columbus's Smart Columbus initiative, as well as providing users with options about their parking, which

ParkSmart has done by providing multiple options that they can use to select where they'd like to park.[2]

In Topp's 1993 research on "*Parking policies to reduce car traffic in German cities***"**, he found that parking guidance systems are doubtlessly useful at reducing the amount of car traffic generated by a search traffic. He also notes that parking spaces generate traffic based on how long they're full, what time of day they are used, how often cars park and leave there and how long people spend searching for parking. Topp also comments that search traffic is often of 50-70% of the total car traffic in a city center and that a parking guidance system should "inform about specific parking garages instead of 'free spaces straight on', because people familiar with a city follow a display only if they know to which parking garage they are being directed." Ultimately, Topp's research informed our decision to incorporate directions into our solution, as ParkSmart wants users to understand where they are going and how they get there.[3]

Bonsall and Palmer's 2004 work on *Modelling drivers' car parking behaviour using data from a travel choice simulator* lead to the development of a parking choice simulator, which allowed them to observe how drivers' searched for parking and what types of decisions they made to look for parking in urban areas. They observed that price, walking time, driving distance, knowledge of the area and search time were important variables in how someone went about searching for parking. These ideas were seminal in producing our final work as we wanted to ensure that ParkSmart accounted for all the factors that someone may care about, when looking for a place to park. They also found that a majority of drivers on their first, unfamiliar journey to an area, preferred to head for an area where they knew there would be a car park, like a rail station, and those who had head to their location first, tended to change their behavior as the trail went on. Our solution allows us to counteract the trend of heading to an area where there might be parking by letting a user know exactly where there is parking.[4]

Parking guidance systems decreased search times during periods of high demand, such as Saturdays and lead to complex shifts in parking search behavior, as described in Polak and Axhausen's 1994 *Measuring the effectiveness of parking guidance systems: a case study of Frankfurt and Mainz.* Their work noted that system buy-in will lead to better benefits for the people of the city, meaning that any solution must be accurate and eventually adopt widespread

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[2] Young, W., Thompson, R. G., & Taylor, M. A. P. (1991). A review of urban car parking models. Transport Reviews, 11(1), 63–84. https://doi.org/10.1080/01441649108716773
[3] Topp, H. H. (1993). Parking policies to reduce car traffic in German cities. Transport Reviews, 13(1), 83–95. https://doi.org/10.1080/01441649308716836
[4] Bonsall, P., & Palmer, I. (2004). Modelling drivers' car parking behaviour using data from a travel choice simulator. Transportation Research Part C: Emerging Technologies, 12(5), 321–347. https://doi.org/10.1016/j.trc.2004.07.013

use across a city. Additionally, their work advised to consider factors affecting the use of the system such as: how information is disseminated; journey characteristics; parking preferences; and the level of familiarity and local knowledge of the driver population.[5]

Finally, Boesefeldt and Kunze's 1982 *Erfahrungen mit der planung und dem einsatz von parkleitsystemen,* explored the results of Germany's first parking guidance system. In Aachen, Germany, where a parking guidance system was installed in the early seventies, less than half of the drivers who are familiar with the city follow the system. This means that, generally any new solution must consider who exactly would be using this system, which as noted by Boesefeldt and Kunze, will largely be first timers to the city. Average search traffic in Aachen dropped from about 25% to about 21% of the total car traffic, but the system is used more often at peak times, meaning that the system is certainly useful in reducing traffic flow. [6]

Current Examples:

In examining the work being done today, we must consider the technological systems available to us and consider the use of their integration. Google, for example, has been combining efforts across its platforms to build a parking guidance system. On their Android devices, in the Google Maps application, users can now select an option that allows them to find parking near their destination. After entering their desired destination into the application, users are presented with a list of nearby parking lots and garages, based on their proximity to their journey's terminus. Upon choosing a nearby parking lot, Google Maps gives them walking directions to their final destination. A solution, like Google's, is a prime example of what is possible given the resources of a large company that has already mapped a large number of the world's parking lots and locations. However, unlike some solutions, Google does not use crowdsourced data to estimate those parking lots' fullness.[7]

Figure 1: Market Validation. These are some of the current examples of what work has been done in the parking prediction space. It is a field just beginning to be explored and a solution like ParkSmart can be on the cutting edge.

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[5] Polak, John & Axhausen, Kay. (1994). MEASURING THE EFFECTIVENESS OF PARKING GUIDANCE SYSTEMS: A CASE STUDY OF FRANKFURT/MAIN. TSU REF. 8 p..
[6] Boesefeldt, J and Kunze, W. 1982. ERFAHRUNGEN MIT DER PLANUNG UND DEM EINSATZ VON PARKLEITSYSTEMEN. Transportation Research Board of Germany. Straßenverkehrstechnik. Volume 26. Issue 4. Pages 99-109.
[7] Gartenberg, Chaim. "Google Maps Will Now Help You Find Parking". *The Verge*, 2017, https://www.theverge.com/2017/8/29/16219704/google-maps-parking-find-lots-garages-update-android.

Alternatively, the multinational car company BMW has partnered with both parking payment platform ParkMobile and the traffic data company INRIX to the industry's first on-street parking availability service. Using historical and up-to-the-minute parking data from both BMW's autonomous vehicles, ParkMobile and INRIX, this service predicts the availability of parking spaces on a given block for drivers and has been integrated into BMW car dashboards. The solution is being implemented with the aim of allowing BMW's autonomous vehicle fleet to, as ParkMobile's CEO puts it, "be able to get into their car knowing exactly where their car will come to rest at the end of their journey." This is a solution that we have tried to emulate for Honda's autonomous vehicle fleet. [8]

Methodology:

In examining all of the previous work that has been done on this topic, we came to a few conclusions about what types of data ParkSmart should include. Through our partnership with both Honda and the city of Columbus, Ohio, ParkSmart was able to incorporate historical vehicle trips, street parking meter transactions, traffic data, consumer parking habits, parking ticket transactions and both real-time spatial and temporal information to build a system that can ultimately be deployed in Honda's fleet of autonomous vehicles and connected cars.

Data Dictionary

Table Name	Description	Type
Summary	Aggregated summary per vehicle per trip. Each ignition cycle generates only one summary record.	Log
Host	Periodic log of host vehicle's internal signal	Log
RvBsm	The messages **received** by the host vehicle from remote vehicle	Log
EvtWarn	Log of all the **events** observed by the host vehicle Each event of interest creates a one-record snapshot of the kinematics	Log
Spat	The messages received from intersection unit. One record each 0.5 sec that is received by the host	Log
RvZone	Relative location of the remote vehicle	Dictionary
RvBasicVehClass	Basic type/class of the remote vehicle	Dictionary
AlertLevel	Level of the event	Dictionary
EventAppId	Type of event/alert	Dictionary

Table 1: Honda Data Dictionary. This is the data dictionary for the initial subset vehicle trips that Honda provided for this project. The relevant kinematic and trip log data was used for our time series model and included information such as brake status, car speed, location & acceleration.

Through our partnership with Honda, ParkSmart was able to work with thousands of vehicle and trip logs, allowing us to see how cars were travelling throughout the city of Columbus. This included aggregated summaries of each vehicle trip, each host vehicle's internal signal and message information, the kinematic events observed by the vehicle, the vehicle's location, and various other information about each vehicle and each event and message it transmitted. Specifically, ParkSmart uses information about the trips such as the car's speed, acceleration, latitude and longitude, brake status, among others. The data was provided by Honda engineers as Excel files and required some data cleaning. By

[8] Heaps, Russ. "BMW Integrates Parkmobile Parking Solutions Across All Vehicle Lines." *Autotrader*, Oct. 2017, www.autotrader.com/car-news/bmw-integrates-parkmobile-parking-solutions-across-269859.

parsing this data down to the relevant portions for parking, ParkSmart uses millions of data points in our time series model to identify whether a spot was likely available or unavailable at a specific point in time.

Through our partnership with Smart Columbus, ParkSmart includes various other datasets. The Smart Columbus initiative is a program, created by a U.S. Department of Transportation grant, where the city of Columbus, Ohio has made much of their transportation data, as well as over 3,200 other datasets about regional infrastructure, geography, political subdivisions, parks, and various other forms of information about the city. Through these datasets, we were able to identify the key pieces of information that would help us build our model.

One of these datasets allowed us to examine roughly nineteen million parking meter transactions, in Columbus, from 2015 through 2017. This dataset provided us with the start and end time for each each meter use, which meter was used, and how much money was paid to use the meter. This dataset would become very important in our forecast model, as ParkSmart used this historical data to create a lookup table that allowed us to look at the percentage of time each meter was in use, based on the day of week, time of day and month.

	Pole	ParkingStartDate	ParkingEndDate	TransactionType	TotalCredit
714	EP200	1/2/2015 7:10	1/2/2015 10:40	Credit Card	2.00
877	NQ387	1/2/2015 8:42	1/2/2015 18:04	Credit Card	3.75
44	EI160	1/1/2015 6:28	1/1/2015 7:10	Cash	0.25
856	NO101	1/2/2015 8:21	1/2/2015 11:21	Credit Card	2.25
381	EA6	1/1/2015 11:55	1/1/2015 13:10	Cash	0.50
997	SO307	1/1/2015 19:14	1/1/2015 19:22	Cash	0.05

Table 2: Parking Meter Transactions: This is a sample of the first thousand rows of the Smart Columbus parking meter transaction dataset from 2015-2017. The dataset contains over nineteen million entries from parking meter transactions across the city of Columbus, Ohio. The dataset contains temporal information about each parking meter, as well as how much was paid and the method of payment.

This dataset would be combined with a few other resources. A dataset detailing the locations and various other information about Columbus's parking meters was used to ensure ParkSmart only used data on working meters, at times that they were in operation. It also allowed us to help direct a user to the closest locations, by allowing us to see where each meter was. Another resource ParkSmart used was a dataset evaluating traffic and parking habits by the company Geotab, a parking-specific data provider. This dataset segmented two years worth of data about the city into hundreds of small geohash zones, which each had various pieces of information about them such as, when the cars within them were looking for parking, how long they spent looking for parking, how many zones they travelled through, while looking for parking, and how much demand there was for parking in that geohash. Ultimately, ParkSmart used this to see the average length of time that cars spent looking for parking, average distance travelled and distribution of when they looked for parking, in each geohash. ParkSmart also uses data on Columbus's distribution of parking tickets, which was segmented by the nearest meters to show our users, where a driver should avoid looking for parking. Ultimately, ParkSmart combines these datasets to develop a score that sends a user to the best location for parking, based on distance, number of meters in an area, average time to park and time.

How It Works:

Using our two models, ParkSmart is able to feed a user our best projected parking location based on what type of information we have available. Essentially, our method explains that if a Honda car has recently been near their destination, then ParkSmart will use the time-series model. Since ParkSmart uses Honda data for this portion, it will have the ability to know if a parking spot is open, which could be eventually implemented in real time, based on the data that is being produced by Honda's cars. Effectively, if a Honda connected car has driven by the location, then ParkSmart will know the availability status of that location. If ParkSmart has selected to use the time-series model and that model is able to find available parking, then ParkSmart will deliver the user directions to the closest meter to the destination. However, alternatively, if the time series model says that parking is not available, then ParkSmart will remove certain nearby meters, based on our time Series model identifying their unavailability and then use the forecast model. Finally, in the case that there is no Honda data nearby, ParkSmart will directly use the forecast model.

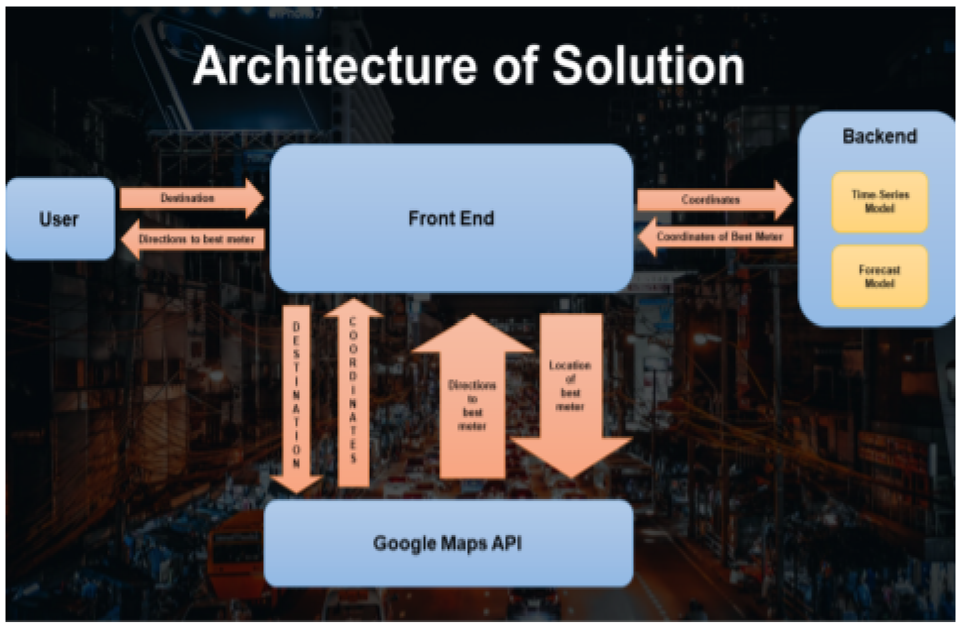

Figure 2: This visualization depicts the architecture of our solution. As described, essentially a user inputs their desired destination and our backend determines what the best parking spot for that user is, using one of two models. Directions to the best meter are then sent to the user through our Front End and Google Maps.

Time Series Model:

Ultimately, this is a time series classification model that separates the data into intervals acting the same way vectors would in a simple classification model. The model trains on the coordinates, velocity, acceleration, brake status, turn signal and lamp usage, as well as various other portions of the trip information. After testing various intervals at different lengths and different types of models, ParkSmart's current model was selected to be the following.

For each unique device and trip, each 30 second period was clustered into a classification of "Available Parking", "Looking for Parking", and "Not Looking for Parking." Because ParkSmart does not have the true search status at each point of the trip, it used knowledge of driving behaviors and laws to make inferences on the statuses. The last interval is classified as "Available Parking" as that period represents that a car was able to find parking. The periods following that where the driver is under fifteen miles per hour, what we defined as the speed limit of a parking lot, and within five blocks of the destination, what we defined as walking distance, are classified as looking for parking but that parking is unavailable at that specific moment. and the remaining periods are classified as cars not looking for parking and do not affect the results of available parking in an area.

If the time series model returns "Available Parking," it returns the closest meter within vicinity of the car. If the model returns "Looking for Parking," the ParkSmart will remove all meters within vicinity of the vehicle and use the forecast model with only the meters that have not been eliminated. If the model returns "Not Looking for Parking," then ParkSmart only use the forecast model.

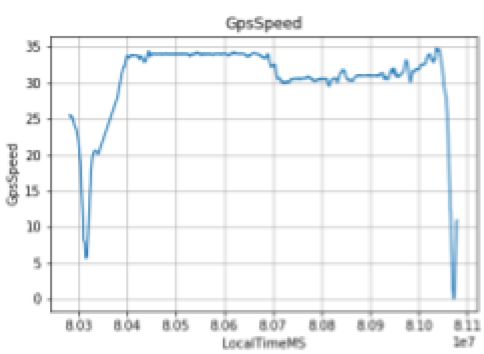

Figure 3: GpsSpeed: GPS Speed over the period of the trip can be calculated into time series statistics

For each trip, the module tsfresh calculates time statistics of recorded time series, such as acceleration or speed. Calculated statistics included factors such as aggregate autocorrelation or absolute sum of changes. Then we used the module to select the most relevant statistics to use as the columns for our feature matrix.

The model used a 80:20 training to testing split to minimize underfitting and overfitting measured by a simple classification loss function. ParkSmart is trained on three different types of models, but the random forest classifier returned the highest rate of validation accuracy at 85% versus the 76% validation accuracy that was obtained through logistic regression.

While our current solution works using historical Honda data, and was trained, tested and validated using previous trip information, the solution that would get implemented into actual Honda vehicles would need to have a live feed of car data. We have created our solution in such a way that this should be implementable, once Honda is ready to deploy the model, as our model assumes we are working with live data. With real time data, we can use specific data from smart Honda cars, that have recently been near our desired destination, and thus use real-time information to both see and estimate whether a spot is still available.

Forecast Model:

Our forecast model is built mainly off of three years of historical Columbus parking meter transactions to look at how often a metered spot was available. We want our users to stay away from areas with a high volume of parked cars and instead park in nearby areas with a higher chance of finding street parking. Segmented by day of week, month and time of day per twenty minute increments, the forecast model incorporates the percent chance of a metered parking spot being full based on the number of cars that parked in that spot in the past at this time.

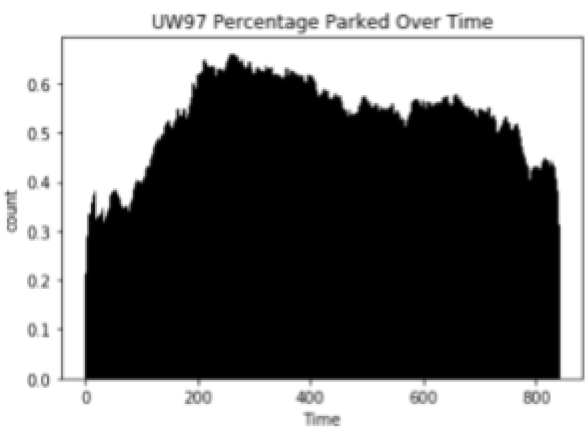

Figure 4: UW97: The probability that a particular meter, UW97, was being parked at each minute in time, during its operating hours (with the opening of 8am scaled to 0). This was the most popular meter in the city and is occupied roughly half of the time during its operating hours..

As an example, if ParkSmart knows that at 3:20pm, on the fourteen January Tuesdays in our dataset, there were thirteen cars parked at meter UW97, the most popular parking meter in Columbus located on the southside of Ohio State University, then ParkSmart will have a user avoid that area. However, if our model finds that there are more likely to be available spots in a nearby meter, then it will direct a user there instead of UW97. Ultimately, our model uses past years to drive predictions for future parking instances through the percentage of time meters had open spots.

However, ParkSmart also is implemented with a clustering algorithm to allow us to better see what kind of parking was available at nearby meters, so ParkSmart could send users to zones with higher parking availability. By implementing on a K-means unsupervised clustering algorithm on the information we had about the city’s parking meters, such as their location, operating hours and costs, we were able to convert over four thousand meters into seventy-seven bins representing neighborhoods. ParkSmart then uses these bins to aggregate parking availability at each day of week, month and twenty minute time interval, within standard Columbus parking meter operating hours. These groupings allowed us to employ a machine learning technique to better provide users with areas where there will be high parking availability, based on proximity to the destination where they wish to park.

Our model takes these percentages and uses the other aforementioned datasets to incorporate average time spent looking for parking, distance to nearby parking and has drivers avoid areas with high ticketing. Using Geotab's Searching For Parking data and the Columbus Police Department's parking ticket database, we examined the locations of potential areas where someone could park and compiled a callable dictionary of how each area performed in those metrics.

Ultimately, this allowed for the development of a metric that rates the places that a user could look for parking based on all of the aforementioned features: nearby meter and zone parking availability at each time, average time spent looking for parking in each geographic zone, distance to nearby parking, and percent of parking tickets given out in an area.

Months	DayOfWeek	TimeOnDay	prob B	prob C	prob E
12	6	740	0.302812	0.268301	0.011278
12	6	760	0.311930	0.278962	0.013158
12	6	780	0.329027	0.282516	0.013158
12	6	800	0.338906	0.276475	0.009398
12	6	820	0.352204	0.279318	0.011278
12	6	840	0.351064	0.279673	0.003759
12	6	860	0.325228	0.275764	0.007519
12	6	880	0.306611	0.271144	0.005639
12	6	900	0.285714	0.275409	0.007519
12	6	920	0.279255	0.284648	0.009398
12	6	940	0.268997	0.287136	0.007519

Table 3: Aggregated Probabilities. Shown in this table are some of the probabilities of a parking spot being available at a certain time for three of our clusters. The Months column represents the month, specifically December in this table. The DayOfWeek column represents the day of the week, specifically Saturday. The TimeOnDay column represents the time of the day in minutes, so 740 represents 12:20pm. The 'prob' columns represent the probability of a spot being available at a certain time in that cluster. So the .302812 represents that 12:20pm on Saturdays in December, there was a ~30% chance that a random spot in cluster B was full.

Finally, when we were testing our ultimate score, we wanted to compare it to what actually happened. Consequently, we randomly sampled some of the actual parking trips from both our Honda and parking meter transactional dataset and tested our model using these actual car trips. For the both of these datasets, we took the locations in which the driver actually found parking and used that as our import location, to see what percentage of the time our model predicted that they should park at that location. We also created a small data set of parking meters, which had open parking at a particular time, to have our model attempt to attempt to predict where someone should park. Through these methods, ParkSmart received a combined 85% testing accuracy on this model.

User Interface:

While our solution is ultimately designed to be used within a Honda vehicle and with their first-party technology, a front end solution was created for the purposes of potentially using this as an web or mobile application in the future. Thus, ParkSmart's current user interface consists of a web application built using Flask, a framework for building complex web applications built on top of Python. We effectively fed our model in as the back end and utilize calls to the Google Maps API for geocoding (converting POI and addresses into geographic coordinates like latitude and longitude), displaying the map and its markers, and turn-by-turn directions.

Our current product is a web application where a user inputs their destination and selects a "Show Me Parking" button on their chosen screen. They are then presented with our model-driven available parking options / suggestions plotted on a map, nearby their destination, including information about the parking such as price and availability. The user then will select their preferred parking option, out of the options provided. As of now, the user will be directed to that parking location by Google Maps, using a customized link that is created with the input origin and destination, as well as the parking suggestion as a waypoint. Upon arrival, the user will be given walking directions to their final destination through Google Maps as well.

Through our work with Honda, we expect that this solution would ultimately be deployed within their fleet of Internet-connected vehicles and thus ParkSmart could be put on a server that would be able to send nearby parking information to the vehicle dashboards.

Figure 5: Current Front End Design. These are some still images from our current platform Front End. As of now, a user inputs their desired destination and they are given a customized link with turn-by-turn directions to their desired parking spot and final destination. ParkSmart was built with the intention of deployment in the dashboard of Honda's fleet of Internet-connected vehicles and is easily able to be converted to that format.

In the future, ParkSmart plans to include forms of non-street parking, such as including available public parking lots and how full those are, such as what Android and INRIX ParkMe's current solution does. We would like to be able to provide our users with as much parking information as possible. Though we feel that metered parking tends to be cheaper and better for users, we feel there is a lot of value in possibly directing them to public parking lots, as our research shows that choice is an important factor in our app's future usage. We also feel that once ParkSmart reaches a critical mass of users, and are in a significant number of cars, that ParkSmart can begin to crowdsource this information and know exactly when certain spots become available. Finally, we also plan to implement a way for the user to be asked how their experience was and confirm that the parking spot was available, for feedback purposes and to better train our model.

Results:

Based on our research, we believe that a parking guidance system, like the one ParkSmart has developed, can save Columbus drivers an average of over 4.5 minutes on each driving trip, allowing them extra time to get to their destination quicker and spend more time shopping at local businesses. We also have calculated that ParkSmart would save the average Columbus driver nearly 1.2 kilometers of driving at the end of their trips. By finding parking quicker, drivers are able to spend less time driving around the city and thus emit less harmful carbon dioxide. According to the United States Environmental Protection Agency, the average passenger vehicle emits about 404 grams of carbon dioxide per mile, meaning that our solution would save about 287 grams of carbon dioxide from being polluted into the atmosphere.[9]

If every metered parking trip in Columbus used our service over one year, we estimate that this would have saved the 54.4 years of time for the six million Columbus drivers searching for parking. We also estimate it would have saved 7,223,189 kilometers of driving distance, which would have saved 1,813,260 kilograms of carbon dioxide emissions from being released into the atmosphere.

Models	Accuracy
LinRegression1	0.759861
LinRegression2	0.75874
RandomForest	0.855977

Table 4: Comparison of Selected Models: We compared multiple time series models to select the one with the best performance. As seen above, the random forest had an 85% testing accuracy.

Our time series model was able to return a 85% validation accuracy, but we also found that 90% of our trip periods were classified as "Not Looking for Parking," so we needed an alternative model to return the closest meter in those cases. Even if we were to obtain live data from every active car in Columbus, only 10% could give us information on parking availability at a 85% accuracy rate. Therefore, we developed a forecast model into the pipeline that would improve the overall accuracy.

For our forecast model, we were able to identify a 74% testing accuracy for our model. This was done by using the initial dataset of individual trips who parked at a specific parking meter and removing the trip we are looking at. Essentially, this meant that we would remove the trip we were examining from our dataset and use that trip to see where our model would tell that person to park, We found that 74% of the time, the model would suggest the area that that person

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[9] "Greenhouse Gas Emissions from a Typical Passenger Vehicle." *EPA*, Environmental Protection Agency, 10 May 2018, www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle.

parked as one of the five best parking zones. However, as the forecast model is simply a chart of what happened historically and how many cars were parked at both a meter and in a zone, at a certain time, then we are simply using this data, alongside the other datasets on parking, to identify the best location. This means that a person may not have necessarily parked in the best location, as there may be high rates of ticketing or high unavailability of parking. The best parking location is somewhat subjective, and although we defined what we think makes the best parking spot, it is thus difficult to test on previous results as there are varied reasons why someone parks in a certain location.

Conclusion:

Since Google, BMW and ParkMobile are all working on a similar problem, ParkSmart is certainly a valuable proposition. By having the opportunity to work alongside Honda engineers and deeply research the problem, our team has navigated our way to a very successful result. Our learning path took us through difficult challenges such as solving how to beat validate our model and select which type of neural network we should use for our time series. However, now that our team better understands the behavioral psychology behind driving, we have identified a solution that we are very happy with. By using our plethora of data, and attempting use even more that did not appear in the final model, our ultimate solution provides nearly everything we would want out of a minimum viable product. Through our back end and front end integration, we have created a solution that is usable today to predict open parking spots in Columbus.

The availability of parking is a large problem that is ripe for a technological solution to solve the issue. Parking is time-intensive, traffic-causing, carbon-emitting, expensive and stressful. Consequently, ParkSmart is an ideal starting point for a larger solution to fix a broken parking system.

By aggregating a large amount of data, users can easily become more informed about their parking options and better know where exactly to go, when looking for parking. Using two different types of models allows us to best project the optimal parking location and thus, ParkSmart can get drivers where they want to go quicker, can help ease congestion and can help drivers avoid areas of high ticketing. Our solution aims to make it so drivers always know where their journey will come to an end.

With the advent of the Digital Age, ParkSmart has the potential to become a large-scale, mass-adopted, crowd-sourced solution where drivers can easily identify open parking locations. If our solution is able to fully integrated into Honda vehicles, then ParkSmart would have the ability to expand our solution to mark open parking spots, in real-time.

Additionally, in the future, we hope to expand upon the choice aspect of our work and provide parking garages and other public lots, in addition to various on street parking spots. We also hope to convert our service into a mobile application, which could give us a wider reach then even Honda integration, and better allow us to crowdsource trips.

However, ultimately ParkSmart proudly boasts of a model with 85% accuracy at predicting if a spot is open. The service can help save Columbus drivers an average of 4.5 minutes on each driving trip, nearly 1.2 kilometers of driving at the end of their trips and prevent about 287 grams of carbon dioxide from being polluted into the atmosphere, per trip. This is certainly striking and can make a major impact on Columbus driver behavior.

Appendix:

The code for this project can be found at https://github.com/clarencelam2000/honda-ucb-parking

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