PITSTOP

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1. Brake model is working
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    - xxx
2. Comparison to mileage based shows a distinct advantage
    - xxx
    - xxx
3. Clear next steps to Achieve…. _____
4. Next steps / Phase 2 to further prove out the model

TL;DR the existing dataset can be used for a brake model

From the existing list of Pitstop prognostic models, it seems that the brake model would be the most applicable to the Nissan dataset as it stands.

How The Brake Model Works

Problem: If brakes wear out it is a safety and regulatory issue, but inspections mean downtime and expense

- Em = kinetic energy of motion, where m = vehicle mass and V = speed of vehicle
- Brakes wear because vehicles must dissipate (convert to heat) their energy of motion Em
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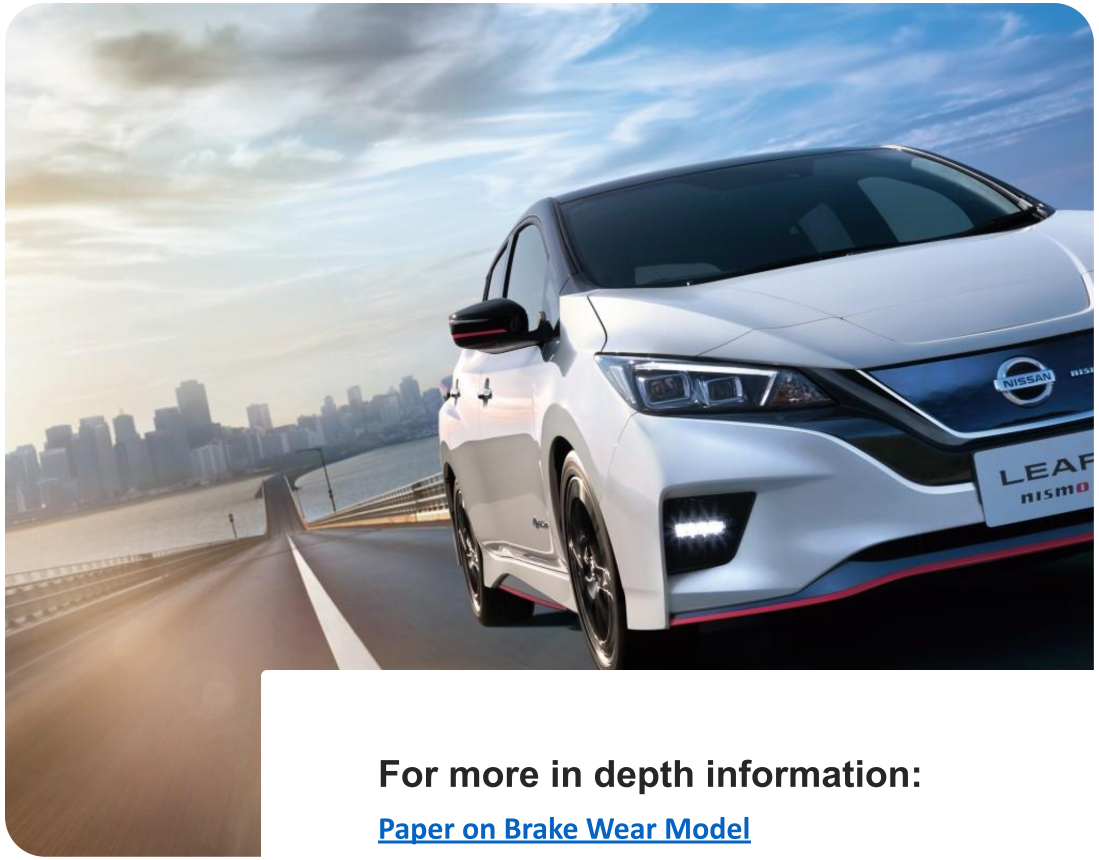
Secret Sauce: Combining telematics, service records with big data and machine learning for example: (i) reliably detect all braking events, (ii) manage cohorts to create correct statistical distributions for energy and for brake maintenance records (iii) Validating the model against maintenance records and known replacements

Steps required to track Brake Wear

1. Detect when braking events occur.
2. Calculating a metric of brake usage per vehicle - energy dissipation per unit distance driven (called the dissipation value).
3. Creating a frequency distribution of the above metric
4. Creating a distribution of brake services as a function of mileage driven
5. Mapping between the distributions to get an estimated mileage for brake
6. Replacement given the dissipation value



For more in depth information:

[Paper on Brake Wear Model]

The data has good attributes for Brake Predictions

High resolution data from a small volume of vehicles (Engineering test fleet)

- Measurements of physical components every week/month (brakes, tires)
- CAN bus data including detailed attributes like brake pressure
- GPS & Acceleration data at high frequencies (~1s or faster)
- Speed, power terrain parameters; torque, coolant, engine oil temp, temp throttle position amongst others (~1s)
- High mileage in short periods of time

Consistent datastreams from large volumes of vehicles (Customer vehicles)

- GPS & Acceleration data at low frequencies (~30s)
- Maintenance records includes brake measurements
- Big Data Volume! Thousands of vehicles with more than 2 brake measurements.

The data has some challenges for Brake Predictions

High resolution data from a small volume of vehicles (Engineering test fleet)

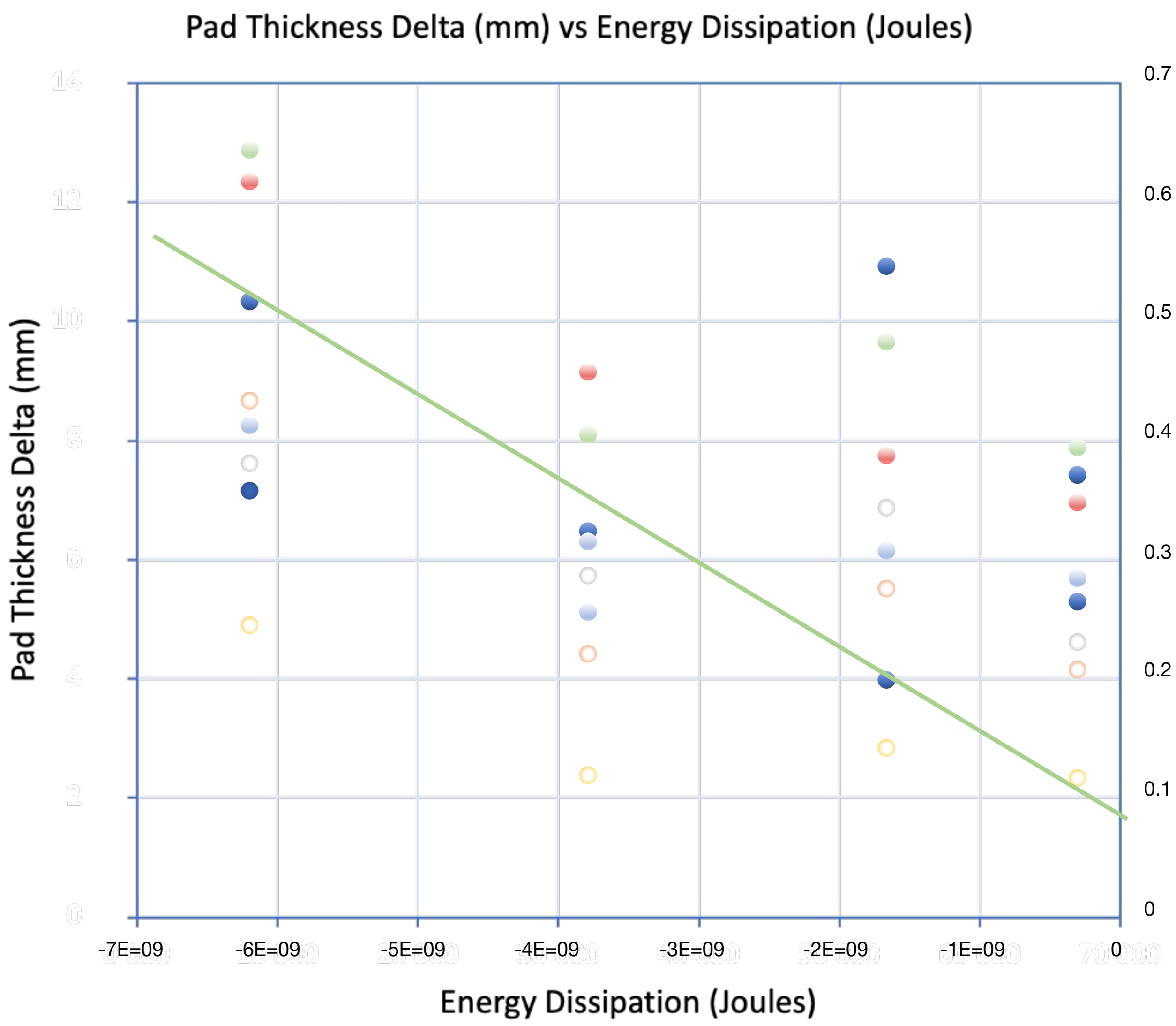
- Trip data does not add up to the total mileage driven. Ex. CTB531 has 10,000 km of accumulated mileage between the first brake measurement and last but there is only ~5000 km's worth of trip data
- There is not enough data volume, both length of time or number of vehicles to perform any meaningful accuracy/validation calculations
- There are cases where either dates, or pad measurements are inconsistent. ex. brake pads increase in thickness over time based on the data

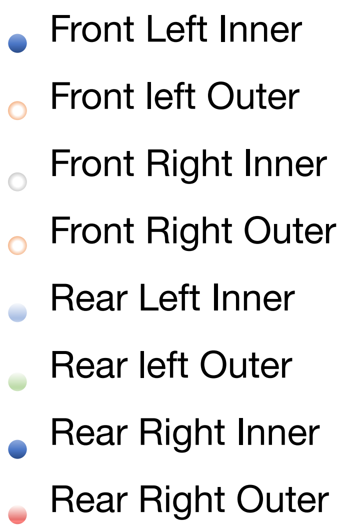
Consistent data streams from large volumes of vehicles (Customer vehicles)

- 30 second sampling frequency can miss out on relevant brake events, making the dissipation calculation less accurate
- Service data dates and odometers don't match up always. Sometimes we see reducing mileage over 1 year which signals incorrect data entry.

Applying the brake model - exploration on FET data

Expectation is satisfied with engineering test fleet which is that more energy dissipation in brakes => more wear between measurements (seen in pad thickness measurement) (CTB546)





Green line is the expected slope

Note: Higher dissipation values are to the left (dissipation is negative by convention)
Note: Data Timespan ~4 months

The brake model is showing Success & validation

Showcase accuracies and strong signs of success with the available dataset

Improvements of the model are better described as reliability rather than accuracy, since it means the model can be adjusted to avoid incorrect assumptions about different vehicle cohorts. However, if we think of accuracy as an average measure of agreement, such as R2, it will amount to the same thing.
Accuracy is not the same as precision. For example, it does not matter if measurements are made to the nearest 100 μ if the standard deviation of the measurement is 1.0 mm.

Next steps to further prove out the brake model

High resolution data helps create accurate dissipation models. However to take advantage of the cohorts via big data there is not enough cases (< 20). This serves as a great start to show that energy dissipation directly correlates with brake wear (slide 7).

However to be statistically relevant a validation test needs to incorporate more cases. The low resolution UIO data helps to put vehicles in cohorts and then plot them on a distribution. An R^2 measure can be made between each vehicle and the “average”. The average is defined as the mileage suggested brake replacement that is provided to every customer.

The accuracy will be the error between the algorithms estimated brake replacement and the average case.

Steps to validate the model

Step 1: calculate the dissipation for each vehicle and assign it to a cohort

Step 2: Each cohort will have a wear pattern which can estimate when a brake pad replacement will be needed. Note: vehicles can change between cohorts as additional data is captured

Cohort distribution

Epsilon(J/km)	n
-1000	3
-1200	5
-1300	7
-1500	7
-1800	11
-1900	5
-2000	2

Table 1.

Expected brake wear at mileage for =-1800

km	W (mm)
1000	-0.18
11000	-1.97
21000	-3.78
31000	-5.58
41000	-7.38
51000	-9.18
61000	-10.97
71000	-12.97

Table 2.

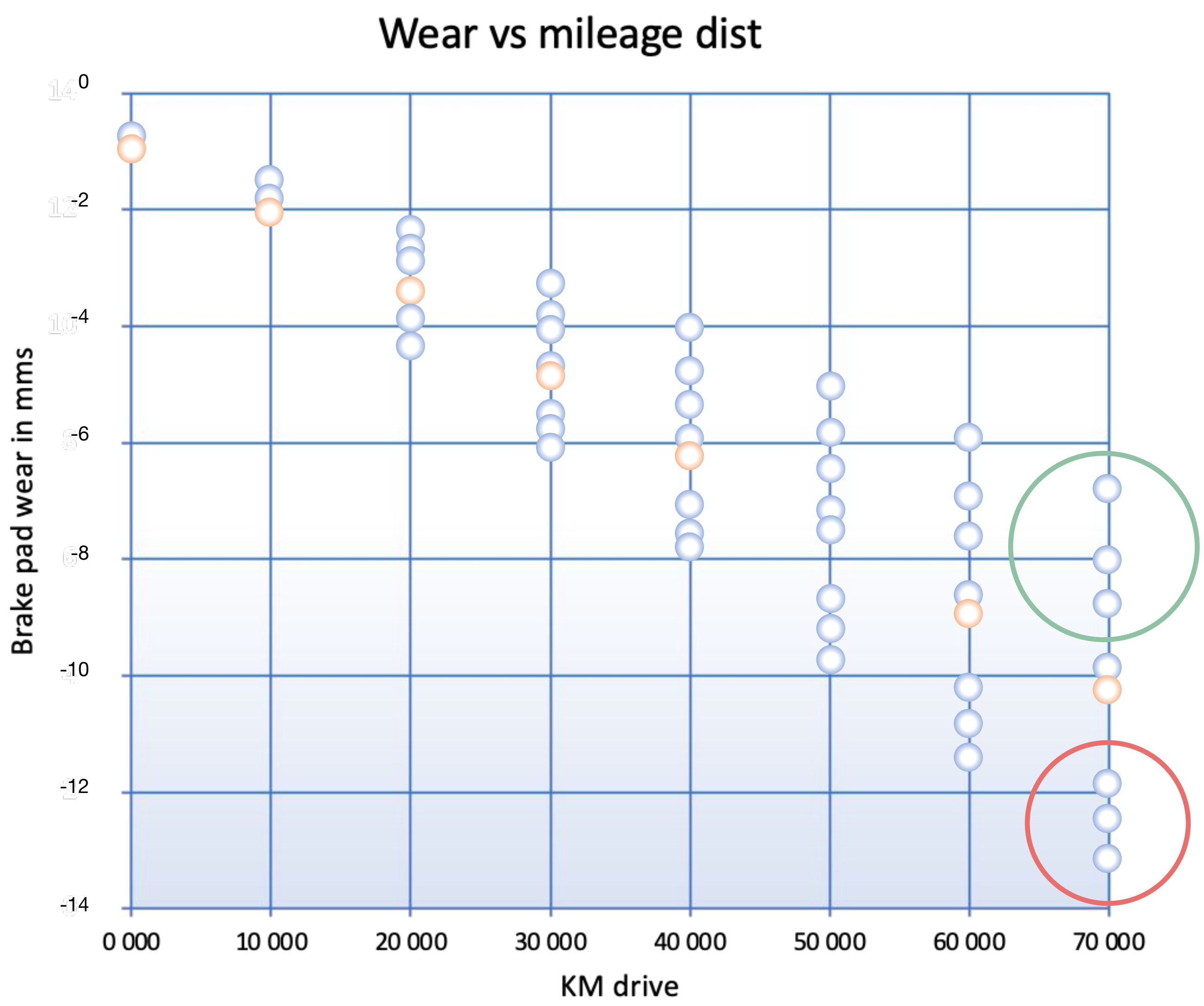
Expected brake wear at mileage for =-1000

km	W (mm)
1000	-0.1
11000	-1.1
21000	-2.1
31000	-3.1
41000	-4.1
51000	-5.1
61000	-6.1
71000	-7.1

Table 3.

Validate the model

Step 3: Comparison between each cohort (blue dotted line) and the average (orange dotted line) will provide an accuracy measure. Cohorts that experience more wear will benefit from safety whereas those that experience less wear will benefit from receiving an accurate suggestion.



Alert would be early. This leads to customer trust issues. “ The dealer just wants me to do service that I don't need”.

Unsafe suggestion that would be too late. Could lead to an accident because of low brakes

64,000 KMs brake replacement suggested

Summary: Expected conclusion of phase 2

We expect phase 2 will prove that the brake model works on the UIO data and be able to showcase a percentage accuracy.
We will use the validation technique described in figure 9 (slide 9).

Based on Pitstops current brake model it seems the accuracy should be within this range x-y% which would be the target.

Nissan Roadmap to Additional Predictions

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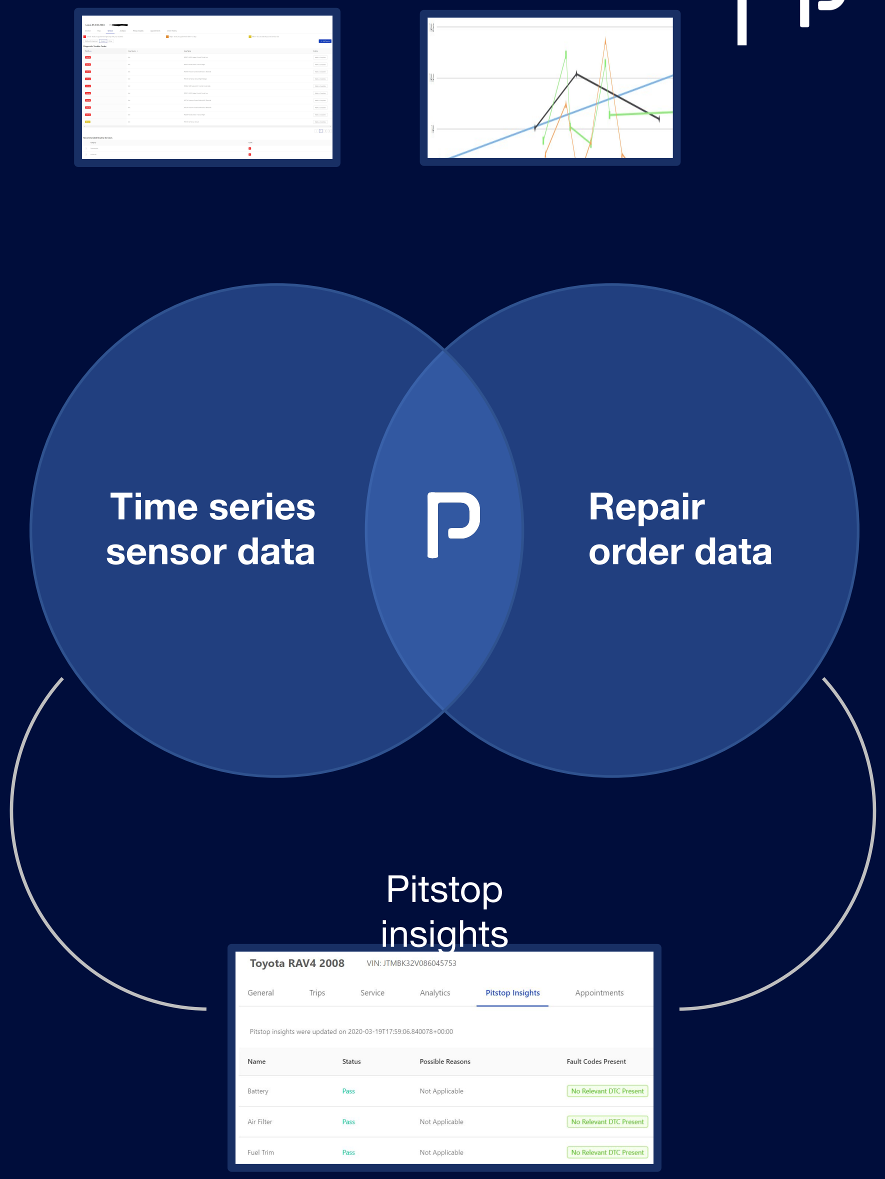
Pitstop’s Existing models and what’s possible

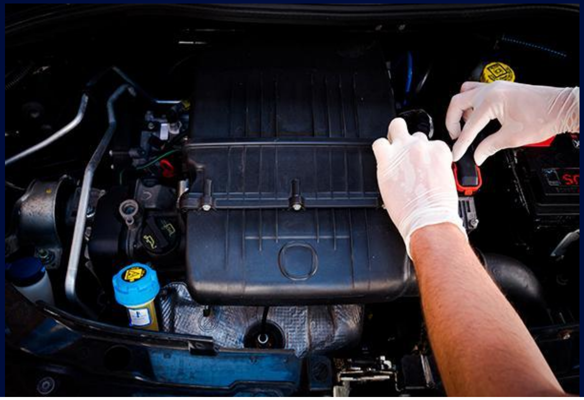
Existing Predictive Algorithms:
- Battery Failure Predictions
- Engine Timing/Combustion Failures
- Transmission failure predictions
- Emissions Analytics
- Diesel Engine Emissions Failures
- Brake Quality Algorithm
- Tire Wear (Under Development)

New Predictive Algorithms:
- EV battery failures & cooling issues
- EV Utilization -Transitioning a fleet to EVs
- Software bug prediction

Highly relevant algorithms.
100% overlap of the top 3 recalls globally with Pitstop’s existing predictive algorithms



Additional Algorithm Details



Battery

- Remove no start scenarios
- Reduce electrical failures Examples include: Battery, Alternator, Starters, Parasitic loads etc..

Engine Control

- Improve Fuel Efficiency
- Manage Engine Fault Priorities
- Examples include: Spark plug, Wires, Injectors, Timing, Crank sensor, O2 sensor, Exhaust, Water-pump etc..

Emissions

- Reduce Diesel Lockouts
- Maintain emissions system before catastrophic failures
- Examples include: DEF, DPF, EGR, Air filter, Hose leaks, Pressure leaks, EVAP issues, Turbo leaks etc..

Brakes

- Improve vehicle safety
- Brake wear analysis across entire fleet
- Examples include: Brake pads, Rotors, hydraulic, pneumatic etc..

Recommendation to extract further value

Sensata Technologies (NYS; ST) became a strategic investor (September 2020) is a leader in sensing solutions and the global market share leader in TPMS

Strategic initiatives include a brake and tire prediction solution for the transportation industry.

Additional Algorithm Details

Problem

Delivery Van Sliding Door was not intended to open and close 100's of times per day - causing bracket failure and eventually body panel damage

Solution:

Utilizing a couple readily available telematics PIDs and repair order information, Pitstop can create a custom algorithm to predict when this failure will occur -avoiding a significant body panel repair cost

The Nissan data has good attributes for models

High resolution data from a small volume of vehicles (Engineering test fleet

- Measurements of physical components every week/month (brakes, tires)
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- GPS & Acceleration data at low frequencies (~30s)
- Maintenance records as long as the customer arrives at the dealer
- Big Data Volume! 10's of thousands of vehicles

The dataset overall does have challenges & gaps

The dataset consists of telematics generated and service data
acceleration, gps at 30 second intervals and odometer
Service records from 30K or so vehicles.

With the current state of telematics data alone solutions related to route optimization and driver risk can be implemented.

With service data alone can assist with getting ahead of defects or looking at inventory and service lane statistics. You can build mileage based prediction models as well.

A value item to be extracted from both data sets is a brake model!
Additional models that maybe extracted include brake and tire wear. These will require extensive analysis and research before being certain that the reliability and accuracy of the models are suitable.

Recommendation to extract further value

Start by asking what types of value propositions are most important to the market.
For example if it's clear that Nissan wants to have models for as many components as possible, then the strategy requires deep edge to cloud implementation. This is capability Pitstop has in the market.

If Nissan decides they want to focus on brakes, batteries and tires then the roadmap will just require specific time-series sensors to be enabled in the data stream.

Pitstop suggests taking a fully integrated approach in order to take advantage of rapid software and data science iteration cycles. New problems will emerge that you cannot currently predict, and hence you need a flexible infrastructure to quickly build new models. This will payback returns as customer satisfaction will improve as well as reduction of recall and warranty costs.

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Custom Algorithm Example

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A wonderful serenity has taken possession of my entire soul,

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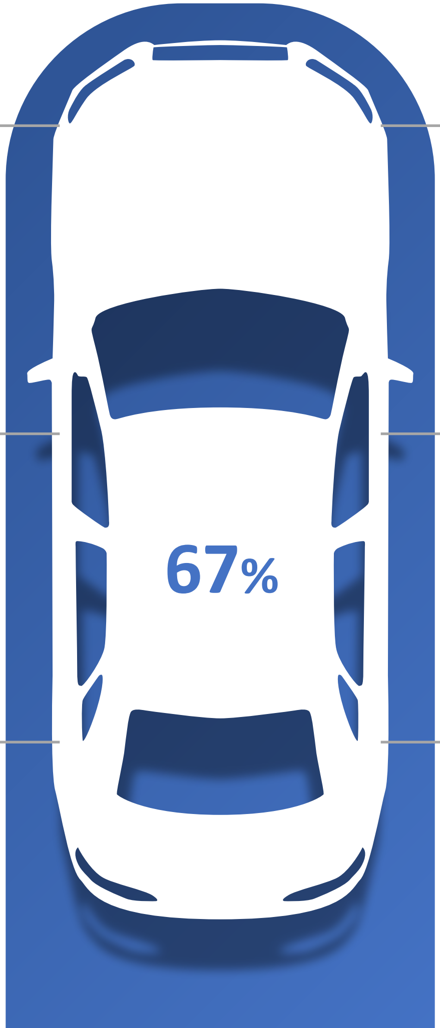

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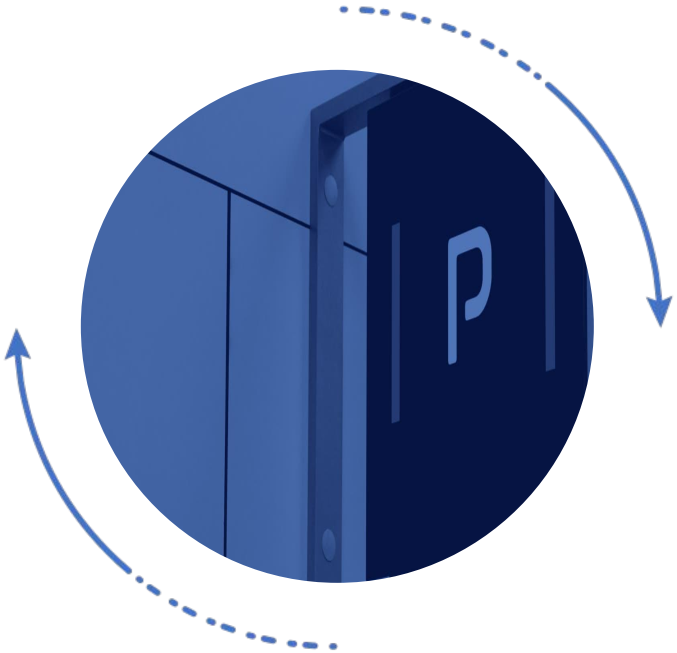

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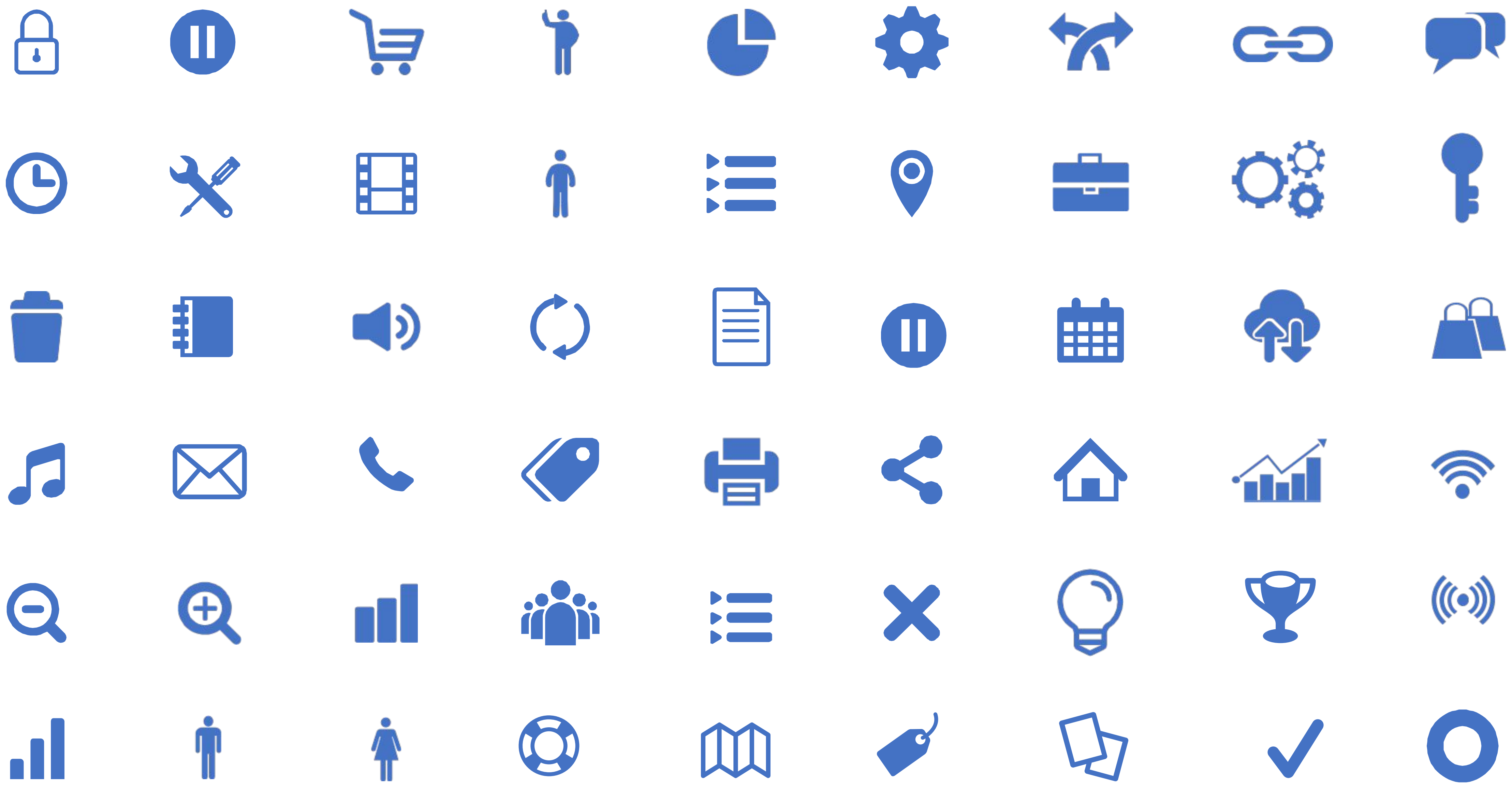

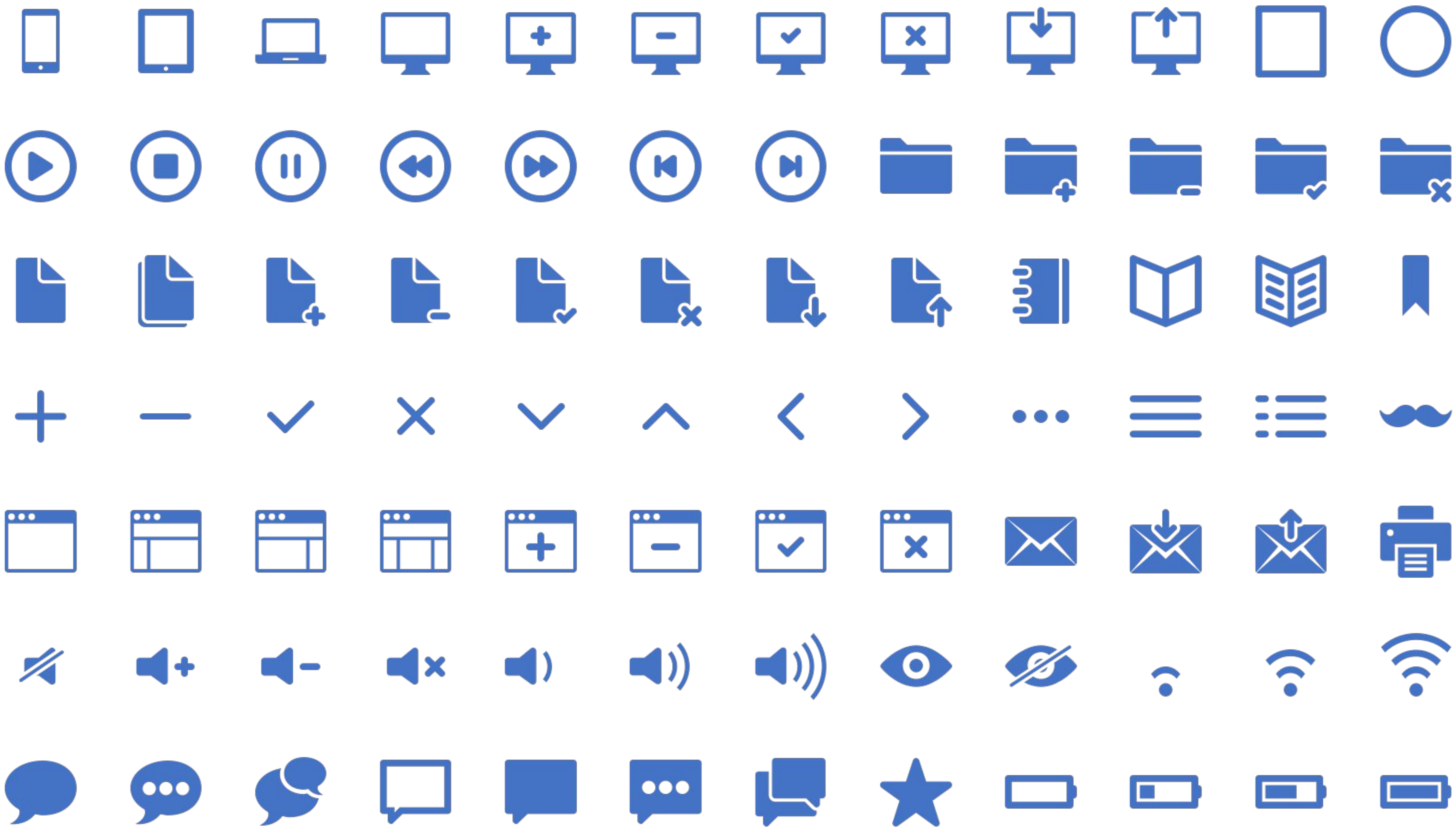

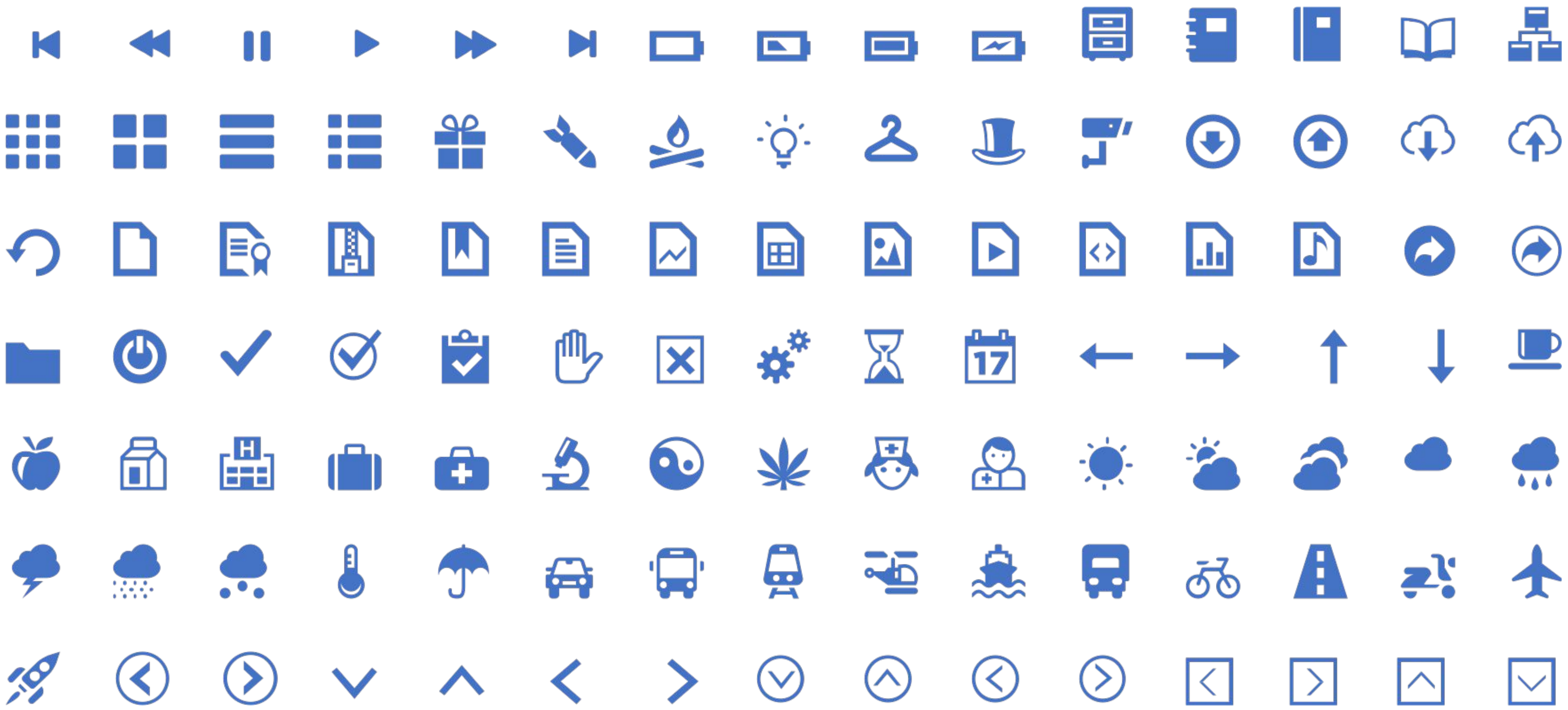
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