Driving Events Identification and Operational Parameters Correlation based on the Analysis of OBD-II Timeseries

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Abstract: On board diagnostics, OBD-II, allowsmonitoring and understanding of the engine operations through continuous access to engine sensors, detection and diagnosis of errors. In this work, we select a set of OBD-II parameters, Short-Term Fuel Trim, Manifold Absolute Pressure, Absolute Throttle Position, Revolutions Per Minute, Calculated Engine Load, Engine Coolant temperature, Vehicle Speed, Catalytic Converter Temperature, to create a set of driving timeseries. A subset of the values belongs to an existing OBD-II dataset with automatic transmission, while the other subset has been retrieved from scratch, using OBD-II, with manual transmission and during characterized driving conditions (cruising, idle and accelerations). We have designed and implemented a set of rules, to recognise three driving events, i.e., idle, gear change, and accelerations in both manual and automatic transmission. The frequency of these events in combination with the parameter values have led to the identification of driving style differences and the impact in fuel consumption. In addition, we have investigated the correlation among the (OBD-II) driving operational parameters during the three driving modes (idle, cruising and acceleration) using the catch22 timeseries analysis framework. The implemented mechanisms are extensible, in terms of considered vehicles, for constant parameter monitoring and cloud-based storing, paving the way for transparent engine status, service maintenance history and other added value services.

1 INTRODUCTION

Monitoring engine operations has attracted researchers to understand the behaviour and improve certain characteristics of the engine operations. Gilman presented a driving assistant system, *Driving Coach,* which monitors parameters to help increase fuel efficiency depending on the driving style (Gilman et al., 2015). Logged OBD-monitored data can be transmitted to a telematics centre via mobile network. This data is used for a prognostics model, as built on correlations among fault codes (cautions/warnings from sensors in the vehicle), to prevent potential components breakdown (Szalay et al., 2015).

In our previous work we have obtained and analysed data through CANBus to calculate the impact of different driving styles on fuel consumption (Rimpas et al., 2020). OBD-II data are also used for provisional or direct maintenance strategies (Peppes et al., 2021; Kulakov et al., 2021; Gajek, 2016; Prytz et al., 2015) by detecting the diagnostic trouble code (DTC) (Beig et al., 2020; Oluwaseyi and Sunday, 2020; Jhou et al., 2013). This can facilitate tracking errors and performing repairs in terms of costs and work. Driving and maintenance records can be stored in a trustworthy manner, providing information for the vehicle performance and reliability. Advice on safe and economical driving has been provided through data analysis for driver assistance and risk prediction and management (Pan et al., 2017). In this work, we select a set of key driving parameters, as retrieved by OBD-II readings, to form *driving timeseries*. An existing third-party dataset is used (Kwak et al., 2016), while we also create our own sets of vehicle operation in different driving modes.

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The main objectives are two-fold:

a) To design and validate rules for the identification of three driving fundamental conditions (idle, gear change in manual and automatic transmission, acceleration).
b) To identify and quantify, based on analysis tools, the existence or lack of relationships (correlation) among driving parameters (such as engine load, RPM, and STFT).

The main paper contribution includes the event-identification rules and their evaluation, in automatic and manual transmission modes. These rules can support labelling / characterization of existing timeseries. The identified events can support the identification of differences in driving styles in an explainable and quantitative manner. This acts complementarily with AI-based works which pursue driving style identification but perform that in an opaque manner (in terms of the timeseries analysis and the interim results). Another contribution of the paper is the identification of the correlation of the operational parameters during different driving modes, using an open, well-known analysis framework (Ezzini et al., 2018). This is complemented by the explanation of the correlations identified from the perspectives of fuel efficiency, and engine preservation.

The structure of the paper is as follows: Section 2 discusses the methodology, describing the operational parameters to be monitored, the event-recognition rules, and the correlation analysis framework. Section 3 describes the identification of driving events per driver, and the association with the driving style. It identifies correlations among the operational parameters under different driving modes. Section 4 discusses the results achieved, the conclusions and the planning for future work.

2 METHODOLOGY

2.1 Datasets and Equipment

We have initially considered the dataset consisting of OBD-II readings from 10 drivers, performing a specified route, starting from Korea university to Seoul world cup stadium and vice versa. Each driver has completed about 46 km of both residential and high road mostly with light traffic. The vehicle employed has been KIA Soul (1600T) with automatic transmission (the dataset is referred as '*KIA dataset*'). The total duration has been 23 hours resulting in over 90,000 values. The OBD-II scanner CarbigsP has been used with Android software. We have observed that the driving pattern of drivers #1, #3, #4, #7, and #10 has more frequent events of interest and less idling segments. For each of them a set of 500 values has been used per trip including all interesting states.

As the dataset lacks labelling in terms of driving mode (for example cruising, idle, acceleration), we have created our own dataset consisting of these modes. For each of these modes we have investigated the correlation among operational parameters. The new (*own*) dataset has been captured on a Toyota iQ 1000cc (1KR-FE engine) model with a manual gearbox. The dataset has been based on a single trip and a single driver. The test has been performed so that the driving conditions and the temperature (25° Celsius) are similar to those of existing dataset. The distance covered, has been a 5-kilometer residential roadway with mixed traffic. ELM327 scanner with ScanMaster 2.1 software has been utilized, connected through cable to a laptop with quad-core CPU, 8GB RAM and 256GB of SSD drive. Sampling has been performed with fixed time intervals of 0.8sec.

2.2 Selection of Engine Operation Parameters

The selection of engine parameters has been based on their importance in the engine operations and their *fundamental* nature. They refer to a physical measure, while other parameters are dependent upon them. They are also *common,* and they can be retrieved using typical OBD-II scanners. The first objective has been whether the selected parameter set, and relevant processing can lead to a) the characterization of driving style, and b) the understanding of the vehicle status for preventive maintenance and error diagnostics. These parameters include the following, and they are summarized in Table 1along with the min and max values.

1. The *Short-Term Fuel Trim (STFT)* as the fuel adjustment by the ECU to handle engine load.
2. The *Manifold Absolute Pressure (MAP)*, revealing the pressure of the air intake.
3. The *Absolute Throttle Position (ATP),* as the percentage of the acceleration pedal pressed by the driver
4. The engine speed as *Revolutions Per Minute (RPM)*, indicating the motor stress.
5. The *Calculated Engine Load (CEL)*.
6. The *Engine Coolant Temperature (ECT)* in the engine block.
7. The *Vehicle Speed*, in Km per hour.
8. The *Fuel Consumption* and the *Instant Fuel Consumption* as a common value.

9. The *Lambda Equivalence Ratio (LER)*, as the air-fuel ratio.
10. The *Catalyst Temperature (CT),* the catalytic converter temperature in degrees Celcius.

Table 1: Selected operational parameters for automatic-manual gearbox, including minimum and maximum values.

Parameter	Min	Max	Unit
Automatic transmission (KIA Dataset)			
STFT	-9	10.2	%
MAP	0	145	kPA
ATP	18	84.3	%
RPM	648	5,529	rpm
CEL	18	97	%
ECT	86	99	°C
Vehicle speed	0	111	Km/h
Manual transmission (Own Dataset)			
STFT	-10	6.5	%
MAP	17	95	kPA
ATP	14.9	40	%
RPM	738	3,869	rpm
CEL	20	96	%
ECT	80	90	°C
Vehicle speed	0	72	Km/h
LER	0.83	1.24	-
CT	502	650	°C

The measurements series include the selected parameters, the timestamp, and the driver. The Lambda Equivalence Ratio (LER) variance has been (statistically) insignificant, as new engines keep the air-fuel ratio close to stoichiometric value (LER≈1), so LER has not been considered further.

2.3 Event Identification Rules

Each driving set consists of discrete, sequential events, related to the driver intentions, the engine and road conditions. While they do not form an exclusive list, typical events include a) the gear change, b) the acceleration and c) the engine idling. The identification of such events (framed with the 'default' *cruising* conditions) can quantitatively characterize a driving session.

For the event identification, the timeseries are sequentially split into small (time) segments with hop length of 1 for gear change and of 2 for idle and acceleration. The behaviour of specific parameters is checked per case, typically comparing the difference of the values between the beginning and the end of each segment. The objective has been to make the rules straightforward and involve only the necessary parameters.

The overall workflow for a) event identification and b) the calculation of the operational parameter correlation is presented in Figure 1.

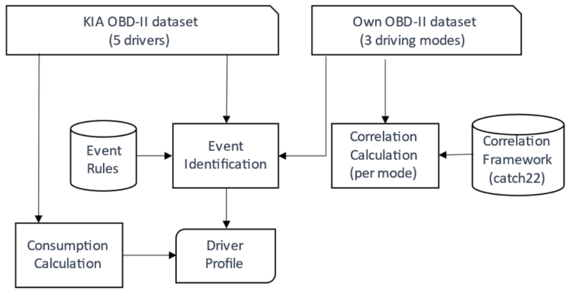

Figure 1: Workflow for event identification and engine operation parameter correlation.

Gear change is characterized by a mild drop in RPM and Vehicle Speed and a decrease in throttle position (approaching the idle throttle position). These observations are expressed as relationships (1), (2) and (3). Timepoint START is the value at the beginning of the segment and END denotes the corresponding value at the segment end.

```
RPM(START)-RPM(END)>0.06*RPM(END)      (1)

VS(START)-VS(END)≥VSdrop,
with VSdrop=0                          (2)

Thr(END)-ThrAtIdle < 0.6*ThrIdle,
with ThrAtIdle=18                      (3)
```

Acceleration is characterized by increased MAP, throttle position and Calculated Engine Load (CEL) values. For each segment, their mean values are compared with a threshold MAP, throttle position and Calculated Engine Load (CEL) [3] values. E.g. *mean(blockMAP(:))* denotes the mean of all MAP values of the segment (block). Another condition is the increasing vehicle speed (implemented through the verification that the values are 'sorted').

```
mean(blockMAP(:))≥ minAccelMAP,
with minAccelMAP=40                    (4)

(mean(blockThr(:))≥ minAccelThr,
with minAccelThr=20                    (5)

(mean(blockALV(:))≥ minAccelALV
with minAccelALV=4                     (6)
issortedrows(blockVS(:))
```

[3] The Load Value measured from CarBigsP app corresponds the Calculated Engine Load (CEL).

Idle is characterized by lower RPM values than a threshold.

```
mean(blockRPM(:))<=RpmIdleMax
```
(7)

While these rules can be applied upon different vehicle models, custom weights and thresholds may apply. The implementation consists of a) timeseries segmentation and b) rule validation with the aim to identify the events. The implementation platform has been Matlab 2021.

2.4 Calculation of the Correlation among Operational Parameters

Engine operation parameters are measured from different modules and pertain to different physical quantities, including temperature, engine load, acceleration, speed, and fuel consumption. Some of them are associated with each other, as they monitor the operation of a single engine, while others are independent. The correlation among them can also change, depending on the driving mode, i.e., cruising, acceleration and idle. Verification of correlation (or lack of it) can pave the way for additional verification of measurements, rules for anomaly detection as well as prediction models.

To identify the correlation among different parameters, we employ timeseries analysis methods to identify and evaluate the relationship and correlation among engine parameters under different driving conditions. Specifically, we extract and compare a set of 22 representative *features* from each of the measured parameters using the catch22 framework. Such features should have strong classification performance and minimal redundancy. They have been selected from a superset of 4791 features from the highly comparable timeseries analysis toolbox using statistical prefiltering, performance filtering and redundancy minimization (Lubba et al., 2019). The features include histograms, period between successive extreme events, minimum of autocorrelation function, centroid of Fourier power spectrum, time-reversibility.

After the extraction of the features, the Euclidean distance per feature pairs has been calculated and normalized in [0, 1]. If the distance is closer to zero, the correlation is stronger and vice versa (distance closer to 1 denotes independence between the parameters).

3 RESULTS

3.1 Driving Events Identification

3.1.1 Automatic Gearbox

Regarding *gear change* identification, we have compared the events resulting from the rules with ground truth, considering the Continuously Variable Transmission (CVT) gearbox and the manual transmission. CVT consists of two variable-diameter pulleys driving each other via a belt (Jawad and Ali, 2020). The diameter ratio of the pulleys determines the current gear ratio. Hence, no gears are required achieving smooth shifting and high durability. Possible adjustments involve intake pressure and load values criteria, as well as the fact that gear change in automatic transmission does not involve withdrawal of the acceleration pedal. However, the risk of converging with deceleration status can affect classification accuracy.

Table 2 presents the event identification results as applied on the dataset with automatic gearbox (KIA). In each cell the first number is the number of the identified events, the second is the number of correctly identified (true positive) and the third the actual number of events.

Table 2: Events identified in the automatic transmission per driver (KIA dataset).

	Gear Changes	Accelerations	Idles
D1	127 (126,134)	47 (46,50)	7 (6,7)
D3	158 (155,163)	57 (55,60)_	2 (2,2)
D4	182 (180,187)	21 (19,22)	12 (11,13)
D7	75 (72,79)	25 (24,27)	5 (5,5)
D10	164 (160,170)	48 (46,50)	9 (8,9)
Total	706 (693,733)	198 (190,209)	35 (32,36)

Regarding *accelerations*, the position of the acceleration pedal is affecting air intake and load values with these three parameters closely related. The time intervals of acceleration and the absolute throttle value suggests the style of acceleration (mild or abrupt). The accuracy reaches 91%, while the rest (9%) is recognized as cruising condition, as the driver accelerates at a very slow rate with low RPM, for fuel efficiency. However, the recognition of these patterns is challenging even for an experienced engineer.

Regarding *idle* identification, 89 % accuracy was achieved, with errors found at low load and throttle values condition correlation. Idle state is identified when the throttle position is stable (13.3 to 14.7%). Challenges emerge at low engine temperature like cold start, where engine runs richer to achieve optimal operating temperature quickly (Zheng et al., 2020).

Additionally, idling in traffic is initially accompanied with higher engine load, because the brake booster is filling with air to enhance braking potential.

Regarding gear changes reaches 95%. With automatic cars, if a steady vehicle speed increment is achieved, gear changes progress normally, so engine speed is sustained at optimal range and torque (Malik and Nandal, 2021). This is the main pattern, affecting fuel consumption and extending engine life, provided that those accelerations are not sharp with increased throttle values.

In terms of driving characterization, accelerations and gear changes can be associated with aggressive driving. Drivers 1, 3 and 10 have similar driving styles according to accelerations, while they differ in the frequency of gear changes. This is affecting fuel consumption and engine stress. Drivers 4 and 7 have similar acceleration patterns with different gear change sequence, which implies aggressive driving for driver 7. For the experiment, idle suggest stopping at traffic lights.

3.1.2 Manual Gearbox

For manual transmission we have considered three typical driving modes a) cruising, b) acceleration, employing our own dataset (Toyota IQ). The values are sampled with a period of 800 ms. The cruising set is characterized by relatively long periods of stable speed with none to mildly active throttle, while the acceleration style being characterized by repeating acceleration (from 0 to approximately 70km/h). The dataset consists mainly of cruising and acceleration (with idle status only in the beginning of the trip). Both aggressive and mild accelerations are taken into consideration. The duration of cruising has been double that of acceleration. The gear changes have been recorded as ‘ground truth’ and compared with events identified by the code.

Table 3 indicates the identified interesting events per driving mode. The number of accelerations is equivalent, while the individual gear changes are approximately 50% less frequent in the acceleration driving mode. This lower frequency can be explained, as the car has been tested specifically for performance (so higher engine speed is required for more horsepower).

Table 3: Events identified in manual transmission per driving mode (own dataset).

	Gear Changes	Accelerations	Idles
Cruising (6.54 min)	37 (36,40)	20 (18,22)	1 (1,1)
Accel (3.17.5 min)	19 (18,21)	15 (14,17)	1 (1,1)
Total	56 (54,61)	35 (32,39)	2 (2,2)

The corresponding accuracies for gear changes is 88.5%, for accelerations 82% and for idles 100%. In principle, the impact upon the operational parameters due to a gear change is less intense in the manual transmission and this proves that a fine-tuning of the weights may achieve better accuracy. Driving with a manual gearbox, requires specific timing in shifting to avoid damaging the gears and clutch. The driver should weigh in the vehicle speed, road incline (if available) and engine load to shift (change gear) within optimal torque range, for maximum performance and fuel efficiency. Even in this case, engine speed (RPM) drop is adequate and easily noticeable while in automatic transmission everything is smoothly handled by the control module with no interruption.

3.2 Fuel Consumption Calculation

To calculate the fuel consumption, since the MAF sensor is not present, the MAP value equivalent is used. Hence, the following equations (8) – (11) are used for automatic and manual transmission (Meseguer et al., 2017; Lightner, 2011):

$$\text{IMAP}= RPM * \frac{MAP}{IAT} \tag{8}$$

$$\text{MAF}= \frac{IMAP}{120} * \frac{VE}{100} * ED * \frac{MM}{R} \tag{9}$$

$$\text{Fuel flow (l/hr)} = \frac{MAF*3{,}600}{AFR*Fd} \tag{10}$$

$$\text{Fuel Cons. (lt/100km)} = \frac{Fuel\ Flow}{Vehicle\ Speed} * 100 \tag{11}$$

IMAP: Intake manifold Sub-parameter
MAF: The equivalent mass air flow in g/s
IAT: Ambient temperature, for KIA dataset of 25°C, based on weather reports according to stated season
VE: Volumetric efficiency of the engine – a typical 85% for both new engines applied (Nutter, 2017)
ED: Engine displacement – 1,591 for Kia Soul and 997 for Toyota iQ (UltimateSpecs, 2021)
MM: Average molecular mass of air (28.97 g/mole)
R: Ideal Gas Constant (8.314 J/ °K * mole)
AFR: Stoichiometric Air Fuel Ratio (14.7)
Fd: Gasoline fuel density, 770kg/m^3 (Acea, 2019)

At Idling, the fuel consumption is not meaningful to calculate as the vehicle speed equals to zero, and only fuel flow is computed. In our previous work, it has been verified that the calculated fuel consumption values are aligned (as mean) with those retrieved from OBD-II (with a percentage of 99%). In Section 4, we discuss the fuel consumption measurements in relation with the driving style.

3.3 Correlations among Engine Operation Parameters

As discussed in Section 2.2., the following parameters have been considered for the estimation of the correlation: 1) Calculated Load Value (CEL), 2) Engine Coolant Temperature (ECT), 3) STFT, 4) Intake MAP, 5) Absolute throttle Position (ATP), 6) Lambda Equivalence Ratio (LER), 7) Catalyst Temperature (CT), 8) Engine RPM, and 9) Vehicle Speed. Table 4 presents the five more and the five less correlated parameters in pairs for the three situations (cruising, idle and acceleration). Each row includes the correlated pair, while the number in parenthesis is the 'correlation index' belonging to [0, 1]. The closer the index is to zero, the more significant the correlation, while 1 indicates independence of the two variables.

Table 4: Correlation calculated in the three driving modes.

	Cruise	Idle	Accel
Most correlated parameters (decreasing correlation)			
#1	MAP, STFT (0.063)	RPM. LER (0.11)	MAP, CEL (0.015)
#2	MAP, ATP (0.12)	RPM, MAP (0.18)	MAP, ATP (0.034)
#3	MAP, LER (0.13)	LER, MAP (0.22)	MAP, LER (0.047)
#4	STFT, LER (0.14)	CT, ATP (0.35)	ATP, CEL (0.048)
#5	STFT, ATP (0.16)	CT, CEL (0.47)	CEL, LER (0.056)
Least correlated parameters (decreasing independence)			
#1	STFT, CT (1)	ECT, MAP (1)	CEL, CT (1)
#2	STFT, RPM (1)	ECT, ATP (1)	RPM, LER (1)
#3	STFT, Speed (1)	ECT, LER (1)	Speed, LER (1)
#4	ECT, LER (0.99)	ECT, CT (1)	CT, LER (0.99)
#5	ECT, MAP (0.98)	ECT, RPM (1)	CT, ATP (0.95)

In cruising, the highest correlation is identified between MAP and the parameters STFT, ATP (Absolute Throttle Position) and LER (Lambda Equivalence Ratio). Similarly, STFT correlates with LER and ATP. On the other hand, the CT (Catalyst Temperature), the RPM and the Speed appear independent of the STFT, where the lack of correlation almost reaches the maximum value (i.e., 1). CT is also independent of LER and MAP.

In the idle status, the correlation is decreased due to its distinctive features. Indeed, during idling there is a constant fuel flow via a forced operation, the battery is not charging properly, engine lubrication is deficient, and the catalytic converter has low temperature. During acceleration strongest correlations appear. MAP is correlated with CEL, the ATP and the LER. Similarly, the CEL is correlated with the ATP and the LER.

4 DISCUSSION

In this section, we combine the observations of Sections 2 and 3 to discuss the impact of the driving style on fuel consumption and vehicle lifecycle. Table 5 includes the mean values (from KIA dataset) of MAP, RPM, speed, load (CEL), ATP and fuel consumption.

Table 5: Engine operation parameters (mean values) and fuel consumption.

Engine operation parameters and fuel consumption (mean values)						
Num.	***MAP***	***RPM***	***Speed***	***CEL***	***ATP***	***Fuel***
1	62.1	1,701.4	37.8	48.3	24.2	12.4
3	38,2	1,877.4	52.6	50.7	28.3	7
4	13.2	1,311.5	21.7	38.9	22.7	5.16
7	53.9	1,642	40.5	42.5	20	9.68
10	56.1	1,743.4	43,3	40.8	23.7	10.3
Cruis	36	2,064.3	38.3	38	19	5.2
Acc.	47,6	2,097.2	39.5	50.1	22	7.4

Driver 1 has the most 'aggressive' driving behaviour according to Tables 4 and 5. Although MAP value is not the highest, the engine speed reaches a maximum of 5.5k RPM which is high and typically contributes to higher fuel consumption (as indicated in Table 5). The mean value of engine load is constrained due to idles states (7 idles have been identified, e.g., due to traffic). Driver 4 is softer on acceleration, achieving a larger number of gear changes so engine is kept at optimal range. We notice that minimum MAP value is zero, like driver 3 and that is an indication that cruising was exploited to highest level, so fuel efficiency is maximum. MAP and ATP are strongly collated to fuel trims (STFT), as indicated in Table 5. So, if they are kept low while cruising, fuel consumption is limited. The analysis of these data results in Table 6. Load values are the same for each driver as they are associated with specific route limitations. Drivers 3 and 4 achieve zero MAP values as both exploit cruising status.

Table 6: MAP, RPM, CEL and ATP minimum and maximum values for driving style characterization.

Differentiation of Data – Kia Soul								
Num	MAP		RPM		CEL		ATP	
	Min	Max	Min	Max	Min	Max	Min	Max
1	21	99	648	5529	18	91	18	78
3	**0**	145	665	3692	18	91	18	82
4	**0**	106	657	3718	18	91	18	78
7	22	99	660	2829	18	91	18	42
10	20	100	663	3483	18	91	18	82

Considering the values of Table 6, the driving style of each driver is characterized in Table 7. Even though driver 3 has the highest MAP, load and throttle values, fuel economy efficiency is second best, as cruising status is vastly utilized. In this case, the stressing upon the vehicle engine is limited, contributing to the extension of the engine lifecycle.

Table 7: Driver aggression categorization.

Most aggressive driver from left to right				
1	10	7	3	4

Similar pattern is followed in our own experiment where the acceleration mode is characterized by greater MAP, load, and ATP values. This results in almost 50% higher fuel consumption than cruising, up. This is aligned with analysis performed in our previous work (Rimpas et al., 2020), where constant acceleration has been associated with engine stressing and decreased fuel efficiency.

5 CONCLUSIONS – FUTURE WORK

The consideration of the OBD-II periodic readings as timeseries measurements has allowed us to apply relevant methodologies a) for driving event identification and b) for parameter correlations. We consider that such as consideration can open new perspectives (in terms of methodologies and tools) in engine operation monitoring and added value services. The event identification rules have proved to be robust, providing reliable results for different drivers, driving modes and automatic / manual transmission. The characterization of the driving style has been verified through parallel calculation of fuel consumption. Similarly, correlation of engine operation parameters correlation per driving mode has been coherent.

As future work we consider further elaboration OBD-II readings. These can include the identification of non-typical values, in the context of preventive maintenance. Sensor operation can allow for prompt vehicle and engine inspection and prevent future malfunctions. The availability of readings, available in the cloud or locally and offered in a trustworthy manner can allow access to a complete and coherent history of the vehicle (Voulkidis, 2022), interesting to potential buyer and state agencies, revealing poor maintenance or unhandled malfunctioning. From another perspective, this work can be combined used with more complex (and opaque) AI/deep learning approaches for the creation of labelled timeseries and to enhance the '*explainability'* of the results.

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