

CarsInLoc

PREDICTION OF THE AVAILABLE NUMBER OF CARS IN A LOCATION

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My data set

In numbers:

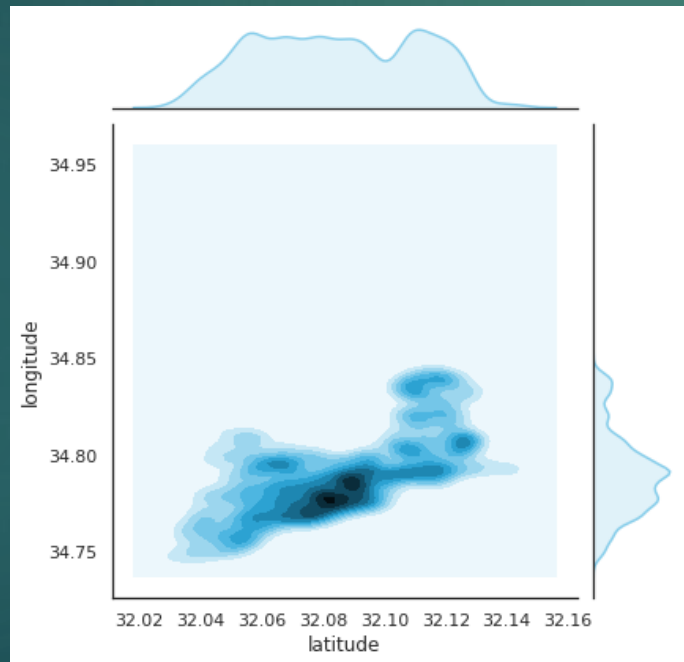
- ▶ Over 6 million rows
- ▶ 18998 timestamps
- ▶ 262 different cars
- ▶ 59456 pairs of coordinates

timestamp	latitude	longitude	total_cars	carsList
2019-01-10 11:45:...	32.09995	34.78794	1	[182]
2019-01-10 11:45:...	32.06567	34.79612	1	[268]
2019-01-10 11:45:...	32.06465	34.80322	1	[106]
2019-01-10 11:45:...	32.05978	34.81034	1	[180]
2019-01-10 11:45:...	32.05133	34.75089	1	[16]
2019-01-10 11:45:...	32.04223	34.7742	1	[72]
2019-01-10 11:45:...	32.04156	34.77128	1	[160]
2019-01-10 11:45:...	32.12373	34.81346	1	[210]
2019-01-10 11:45:...	32.11874	34.83406	1	[136]
2019-01-10 11:45:...	32.03351	34.75509	1	[27]
2019-01-10 11:45:...	32.14288	34.79361	1	[75]
2019-01-10 11:45:...	32.14306	34.79729	1	[132]
2019-01-10 11:45:...	32.083175	34.776552	0	[]
2019-01-10 11:45:...	32.088379	34.775111	0	[]
2019-01-10 11:45:...	32.074877	34.773515	0	[]
2019-01-10 11:45:...	32.098603	34.778565	0	[]
2019-01-10 11:45:...	32.09478	34.79728	0	[]
2019-01-10 11:45:...	32.098032	34.798089	0	[]
2019-01-10 11:45:...	32.12047	34.800318	0	[]
2019-01-10 11:45:...	32.04409	34.80421	0	[]

Use case

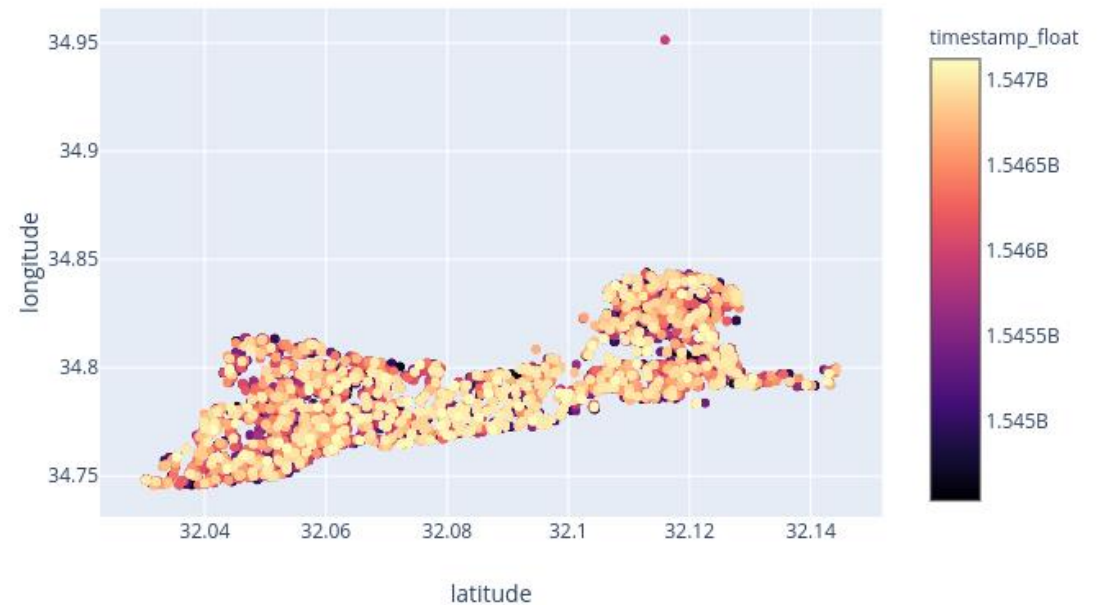
Use case I (Discontinued)

- Prediction of the location of a single car



Density map for car 182

Use case II



Temporal evolution of locations for car 182

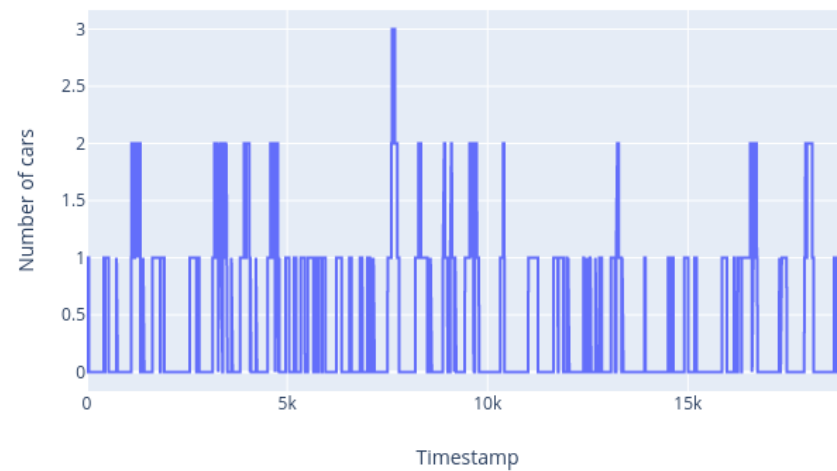
Use case

Use case I (Discontinued)

Use case II

- Prediction of the numbers of cars in one particular location

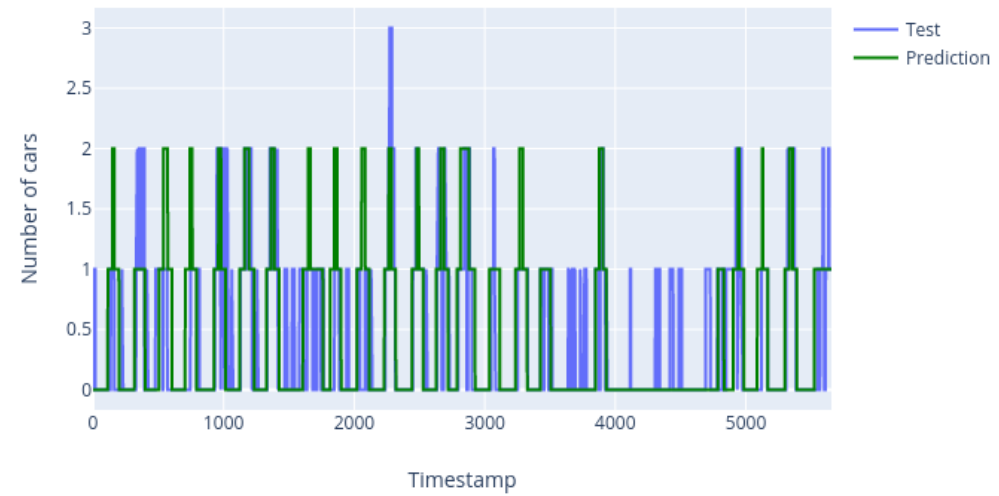
Temporal evolution of the number of cars in (32.072323, 34.790555)



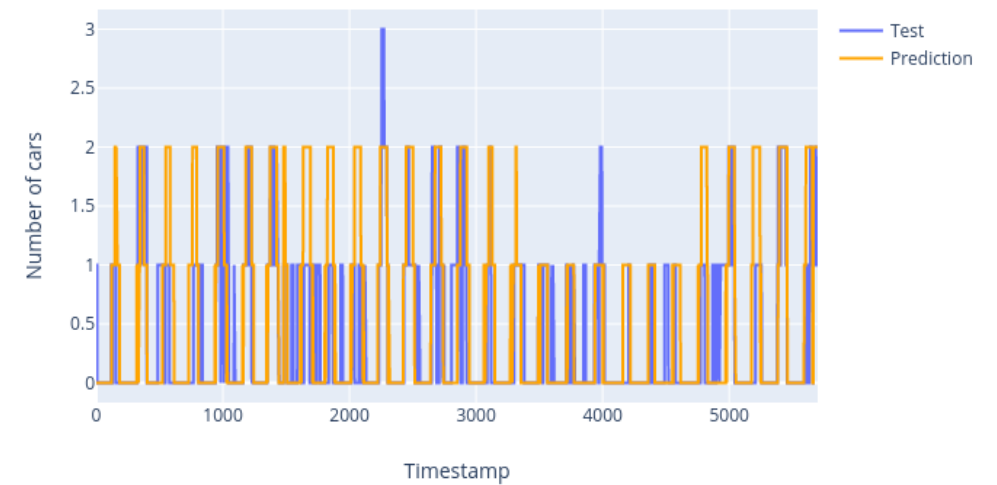
Solution

	ML algorithm	DL Algorithm
Accuracy	73.07%	72.51%
Correlation	61.01%	60.06%

Machine learning algorithm evaluation



Deep learning algorithm evaluation



Architectural Decisions

- ▶ PySpark and Pandas
- ▶ Data is stored locally in my PC as parquet files
- ▶ Keras and Apache Spark ML

Data quality assessment

Check :

- ▶ Ranges
- ▶ Empty cells

+-----+ avg(total_cars) +-----+ 0.6432291962782604 +-----+		
+-----+-----+-----+ avg(latitude) min(latitude) max(latitude) +-----+-----+-----+		
32.083372700257634	31.95223	32.14566
+-----+-----+-----+		
+-----+-----+-----+ avg(longitude) min(longitude) max(longitude) +-----+-----+-----+		
34.78898859070444	34.72998	34.95142
+-----+-----+-----+		

Get useful information:

- ▶ Number of cars, locations and timestamps

Data pre-processing (Use case I)

timestamp	latitude	longitude	total_cars	carsList
2019-01-10 11:45:...	32.09995	34.78794	1	[182]
2019-01-10 11:45:...	32.06567	34.79612	1	[268]
2019-01-10 11:45:...	32.06465	34.80322	1	[106]
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2019-01-10 11:45:...	32.04223	34.7742	1	[72]
2019-01-10 11:45:...	32.04156	34.77128	1	[160]
2019-01-10 11:45:...	32.12373	34.81346	1	[210]
2019-01-10 11:45:...	32.11874	34.83406	1	[136]
2019-01-10 11:45:...	32.03351	34.75509	1	[27]
2019-01-10 11:45:...	32.14288	34.79361	1	[75]
2019-01-10 11:45:...	32.14306	34.79729	1	[132]
2019-01-10 11:45:...	32.083175	34.776552	0	[]
2019-01-10 11:45:...	32.088379	34.775111	0	[]
2019-01-10 11:45:...	32.074877	34.773515	0	[]
2019-01-10 11:45:...	32.098603	34.778565	0	[]
2019-01-10 11:45:...	32.09478	34.79728	0	[]
2019-01-10 11:45:...	32.098032	34.798089	0	[]
2019-01-10 11:45:...	32.12047	34.800318	0	[]
2019-01-10 11:45:...	32.04409	34.80421	0	[]

Initial
DF

	timestamp	latitude	longitude	total_cars	carsList
2019-01-10	11:45:...	32.09995	34.78794	1	[182]
2019-01-10	11:45:...	32.06567	34.79612	1	[268]
2019-01-10	11:45:...	32.06465	34.80322	1	[106]
2019-01-10	11:45:...	32.05978	34.81034	1	[180]
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2019-01-10	11:45:...	32.083175	34.776552	0	[]
2019-01-10	11:45:...	32.088379	34.775111	0	[]
2019-01-10	11:45:...	32.074877	34.773515	0	[]
2019-01-10	11:45:...	32.098603	34.778565	0	[]
2019-01-10	11:45:...	32.09478	34.79728	0	[]
2019-01-10	11:45:...	32.098032	34.798089	0	[]
2019-01-10	11:45:...	32.12047	34.800318	0	[]
2019-01-10	11:45:...	32.04409	34.80421	0	[]

Initial
DF

String processing

Separate labels into columns

[illegible]

Initial
DF

timestamp	latitude	longitude
2018-12-11 15:48:...	32.083	34.7806
2018-12-11 15:50:...	32.12093	34.81254
2018-12-11 15:53:...	32.04533	34.7819
2018-12-11 15:53:...	32.035393	34.75873
2018-12-11 15:57:...	32.092	34.79579
2018-12-11 15:57:...	32.106566	34.797869
2018-12-11 16:03:...	32.050287	34.752289
2018-12-11 16:03:...	32.12093	34.81254
2018-12-11 16:03:...	32.10877	34.83471
2018-12-11 16:09:...	32.056237	34.769956
2018-12-11 16:20:...	32.12093	34.81254
2018-12-11 16:22:...	32.087613	34.784496
2018-12-11 16:22:...	32.076339	34.78686

Separate labels into columns

[illegible]

Data pre-processing (Use case II)

timestamp	latitude	longitude	total_cars	carsList
2019-01-10 11:45:...	32.09995	34.78794	1	[182]
2019-01-10 11:45:...	32.06567	34.79612	1	[268]
2019-01-10 11:45:...	32.06465	34.80322	1	[106]
2019-01-10 11:45:...	32.05978	34.81034	1	[180]
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2019-01-10 11:45:...	32.074877	34.773515	0	[]
2019-01-10 11:45:...	32.098603	34.778565	0	[]
2019-01-10 11:45:...	32.09478	34.79728	0	[]
2019-01-10 11:45:...	32.098032	34.798089	0	[]
2019-01-10 11:45:...	32.12047	34.800318	0	[]
2019-01-10 11:45:...	32.04409	34.80421	0	[]

Initial
DF

Filter by latitude
and longitude



timestamp	total_cars
2018-12-11 15:48:...	1
2018-12-11 15:50:...	1
2018-12-11 15:53:...	1
2018-12-11 15:55:...	1
2018-12-11 15:57:...	1
2018-12-11 15:59:...	1
2018-12-11 16:01:...	1
2018-12-11 16:03:...	1
2018-12-11 16:05:...	1
2018-12-11 16:07:...	1

Feature Engineering

timestamp	total_cars
2018-12-11 15:48:...	1
2018-12-11 15:50:...	1
2018-12-11 15:53:...	1
2018-12-11 15:55:...	1
2018-12-11 15:57:...	1
2018-12-11 15:59:...	1
2018-12-11 16:01:...	1
2018-12-11 16:03:...	1
2018-12-11 16:05:...	1
2018-12-11 16:07:...	1

Separate timestamps into different columns



timestamp	total_cars	minute	hour	day	month	season	year	total_cars_int
2018-12-11 15:48:...	1	48	15	11	12	4	2018	1
2018-12-11 15:50:...	1	50	15	11	12	4	2018	1
2018-12-11 15:53:...	1	53	15	11	12	4	2018	1
2018-12-11 15:55:...	1	55	15	11	12	4	2018	1
2018-12-11 15:57:...	1	57	15	11	12	4	2018	1
2018-12-11 15:59:...	1	59	15	11	12	4	2018	1
2018-12-11 16:01:...	1	1	16	11	12	4	2018	1
2018-12-11 16:03:...	1	3	16	11	12	4	2018	1
2018-12-11 16:05:...	1	5	16	11	12	4	2018	1
2018-12-11 16:07:...	1	7	16	11	12	4	2018	1
2018-12-11 16:09:...	1	9	16	11	12	4	2018	1
2018-12-11 16:11:...	1	11	16	11	12	4	2018	1
2018-12-11 16:13:...	1	13	16	11	12	4	2018	1

Feature Engineering (for ML algo.)

Add features
columns

timestamp	total_cars	minute	hour	day	month	season	year	total_cars_int	features
2018-12-11 15:48:...	1	48	15	11	12	4	2018	1	[48.0,15.0,11.0,1...
2018-12-11 15:50:...	1	50	15	11	12	4	2018	1	[50.0,15.0,11.0,1...
2018-12-11 15:53:...	1	53	15	11	12	4	2018	1	[53.0,15.0,11.0,1...
2018-12-11 15:55:...	1	55	15	11	12	4	2018	1	[55.0,15.0,11.0,1...
2018-12-11 15:57:...	1	57	15	11	12	4	2018	1	[57.0,15.0,11.0,1...
2018-12-11 15:59:...	1	59	15	11	12	4	2018	1	[59.0,15.0,11.0,1...
2018-12-11 16:01:...	1	1	16	11	12	4	2018	1	[1.0,16.0,11.0,12...
2018-12-11 16:03:...	1	3	16	11	12	4	2018	1	[3.0,16.0,11.0,12...
2018-12-11 16:05:...	1	5	16	11	12	4	2018	1	[5.0,16.0,11.0,12...
2018-12-11 16:07:...	1	7	16	11	12	4	2018	1	[7.0,16.0,11.0,12...
2018-12-11 16:09:...	1	9	16	11	12	4	2018	1	[9.0,16.0,11.0,12...
2018-12-11 16:11:...	1	11	16	11	12	4	2018	1	[11.0,16.0,11.0,1...
2018-12-11 16:13:...	1	13	16	11	12	4	2018	1	[13.0,16.0,11.0,1...
2018-12-11 16:16:...	1	16	16	11	12	4	2018	1	[16.0,16.0,11.0,1...
2018-12-11 16:18:...	1	18	16	11	12	4	2018	1	[18.0,16.0,11.0,1...

Feature Engineering (for DL algo.)

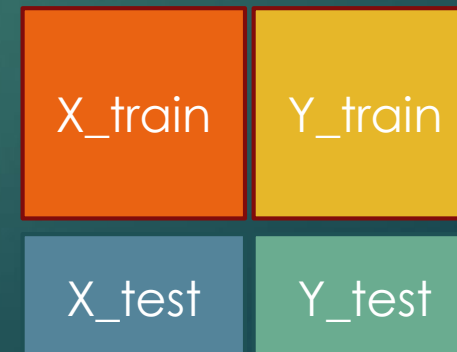
One-hot encoder for season column

Standard scaling

Split into X and Y (input and output)

Split into Train and Test set

timestamp	total_cars	minute	hour	day	month	season	year	total_cars_int
2018-12-11 15:48:...	1	48	15	11	12	4	2018	1
2018-12-11 15:50:...	1	50	15	11	12	4	2018	1
2018-12-11 15:53:...	1	53	15	11	12	4	2018	1
2018-12-11 15:55:...	1	55	15	11	12	4	2018	1
2018-12-11 15:57:...	1	57	15	11	12	4	2018	1
2018-12-11 15:59:...	1	59	15	11	12	4	2018	1
2018-12-11 16:01:...	1	1	16	11	12	4	2018	1
2018-12-11 16:03:...	1	3	16	11	12	4	2018	1
2018-12-11 16:05:...	1	5	16	11	12	4	2018	1
2018-12-11 16:07:...	1	7	16	11	12	4	2018	1
2018-12-11 16:09:...	1	9	16	11	12	4	2018	1
2018-12-11 16:11:...	1	11	16	11	12	4	2018	1
2018-12-11 16:13:...	1	13	16	11	12	4	2018	1



Model Algorithm

Machine Learning

- ▶ Decision Tree Regressor
 - ▶ Feature importance

	idx	name	score
1	1	hour	0.726897
2	2	day	0.271512
0	0	minute	0.001591
3	3	month	0.000000
4	4	season	0.000000
5	5	year	0.000000

Deep Learning

- ▶ 4 dense layers (2 relu, tanh and sigmoid)
- ▶ Compiler:
 - ▶ Optimizer: adam
 - ▶ Loss: binary_crossentropy
 - ▶ Metric: accuracy
- ▶ 10 epochs
- ▶ Final step:
 - ▶ Loss: 0.1364
 - ▶ Accuracy: 0.7408

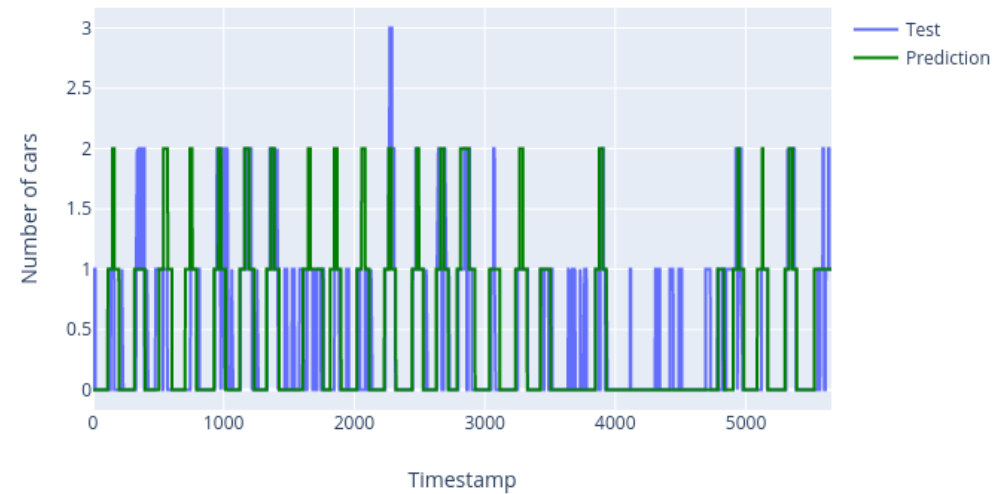
Model performance and indicators

$$\text{Accuracy} = \frac{\text{Timestamps in which the prediction is correct}}{\text{Number of timestamps}}$$

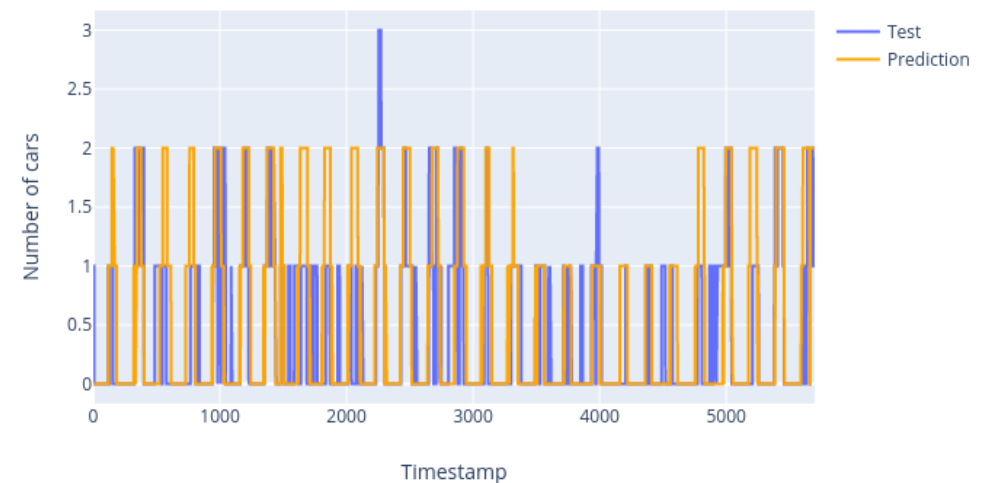
	ML algorithm	DL Algorithm
Accuracy	73.07%	72.51%
Correlation	0.6101	0.6006

Pearson correlation between the test set and the predictions

Machine learning algorithm evaluation



Deep learning algorithm evaluation



Thanks!