Data Manipulation

File Formats

.CSV

```
"name", "surname", "email", "phone"
"Herminia", "Marshall", "herminia.marshall@example.com", "678-313-8625"
"Bernice", "Richardson", "bernice.richardson@example.com", "406-640-0952"
"Maeleachlainn", "Albertson", "maeleachlainn.albertson@example.com", "936-514-5533"
"Laloecen", "Darwin", "laloecen.darwin@example.com", "772-216-4633"
"Shib", "Payton", "shib.payton@example.com", "817-657-1845"
"Marcos", "Bertolini", "marcos.bertolini@example.com", "209-977-7112"
"Daniël", "Teague", "daniël.teague@example.com", "773-750-0852"
"Ikaros", "Garber", "ikaros.garber@example.com", "615-289-1387"
"Regulus", "Cornell", "regulus.cornell@example.com", "832-572-5442"
"Lars", "Simen", "lars.simen@example.com", "843-441-7001"
```

data_csv = pd.read_csv("path/to/file/users.csv")

.tsv

```
"name" "surname" "email" "phone"
"Herminia" "Marshall" "herminia.marshall@example.com" "678-313-8625"
"Bernice" "Richardson" "bernice.richardson@example.com" "406-640-0952"
"Maeleachlainn" "Albertson" "maeleachlainn.albertson@example.com" "936-514-5533"
"Laloecen" "Darwin" "laloecen.darwin@example.com" "772-216-4633"
"Shib" "Payton" "shib.payton@example.com" "817-657-1845"
"Marcos" "Bertolini" "marcos.bertolini@example.com" "209-977-7112"
"Daniël" "Teague" "daniël.teague@example.com" "773-750-0852"
"Ikaros" "Garber" "ikaros.garber@example.com" "615-289-1387"
"Regulus" "Cornell" "regulus.cornell@example.com" "832-572-5442"
"Lars" "Simen" "lars.simen@example.com" "843-441-7001"
```

```
data_tsv = pd.read_csv("path/to/file/users.tsv", sep="\t")
```

.json

```
data_json = pd.read_json("path/to/file/users.json")
```

.xlsx

```
data_xlsx = pd.read_excel("path/to/file/users.xlsx")
```

SQL

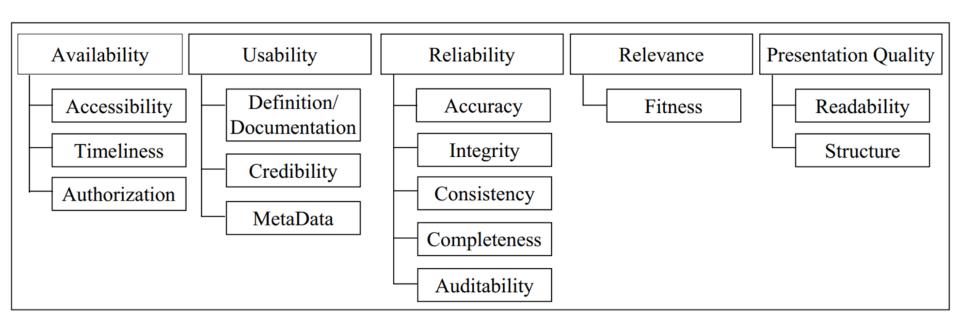
```
conn = sql.connect("path/to/file/users.db")
data_sql = pd.read_sql("SELECT * FROM users;", conn)
conn.close()
```

URL

```
data_url = pd.read_csv("https://example.com/path/to/file/users.csv")
```

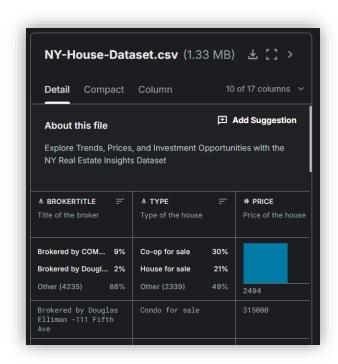
How to assess data quality

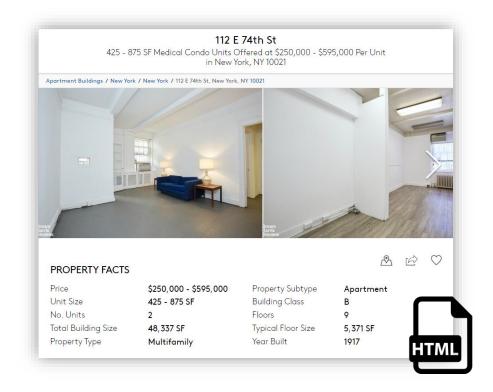
How to assess data quality



Availability

Accessibility





Timeliness



Timeliness



Timeliness



Authorization

otodem Analytics

Authorization

otodem Analytics

1899 zł /30 dni

dostępny dla deweloperów współpracujących z obido

Authorization

2. Postanowienia Ogólne

- 3. Treści publikowane w Serwisie, w tym w szczególności Ogłoszenia, niezależnie od ich formy, tj. materiały tekstowe, graficzne oraz wideo, są przedmiotem ochrony praw własności intelektualnej, w tym prawa autorskiego oraz praw własności przemysłowej, Grupy OLX, Użytkowników lub osób trzecich. Zabrania się w szczególności: a. jakiegokolwiek wykorzystywania tych treści bez pisemnej zgody uprawnionych; b. jakiegokolwiek agregowania i przetwarzania danych oraz innych informacji dostępnych w Serwisie w celu ich dalszego udostępniania osobom trzecim w ramach innych serwisów internetowych jak i poza Internetem;
 - c. wykorzystywania oznaczeń Serwisu oraz Grupy OLX, w tym charakterystycznych elementów grafiki bez zgody Grupy OLX.

Usability

Credibility



Wyniki egzaminu maturalnego w 2024 roku

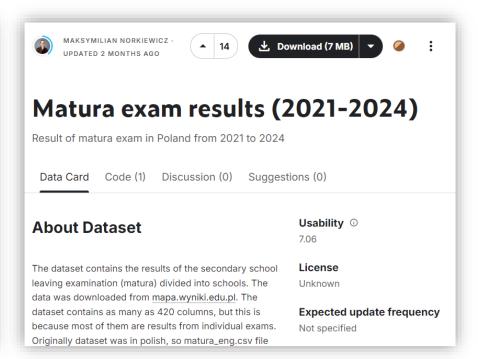
- Wstępne informacje o wynikach egzaminu maturalnego 2024
- Wstępne informacje o wynikach egzaminu maturalnego 2024 CENTYLE
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY POL
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY ENG
- Wyniki egzaminu maturalnego 2024 PREZENTACJA
- Mapki z wynikami egzaminu maturalnego

Credibility



Wyniki egzaminu maturalnego w 2024 roku

- Wstępne informacje o wynikach egzaminu maturalnego 2024
- Wstępne informacje o wynikach egzaminu maturalnego 2024 CENTYLE
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY POL
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY ENG
- Wyniki egzaminu maturalnego 2024 PREZENTACJA
- Mapki z wynikami egzaminu maturalnego





Credibility





Wyniki egzaminu maturalnego w 2024 roku

- Wstępne informacje o wynikach egzaminu maturalnego 2024
- Wstępne informacje o wynikach egzaminu maturalnego 2024 CENTYLE
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY POL
- Wstępne informacje o wynikach egzaminu maturalnego 2024 STANINY ENG
- Wyniki egzaminu maturalnego 2024 PREZENTACJA
- Mapki z wynikami egzaminu maturalnego









Matura exam results (2021-2024)

Result of matura exam in Poland from 2021 to 2024

Data Card

Code (1)

Discussion (0)

Suggestions (0)

About Dataset

The dataset contains the results of the secondary school leaving examination (matura) divided into schools. The data was downloaded from mapa.wyniki.edu.pl. The dataset contains as many as 420 columns, but this is because most of them are results from individual exams. Originally dataset was in polish, so matura_eng.csv file

Usability ①

7.06

License

Unknown

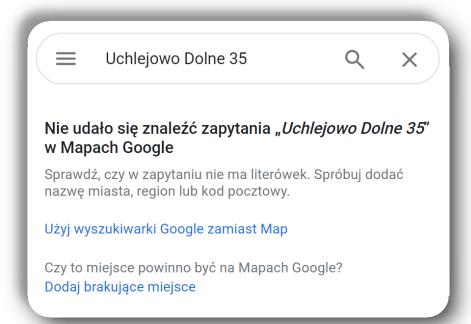
Expected update frequency

Not specified

Reliability

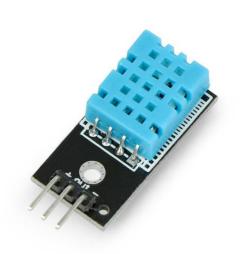
	name	surname	address
0	Kevin	McCallistera	Uchlejowo Dolne 35

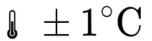
	name	surname	address
0	Kevin	McCallistera	Uchlejowo Dolne 35

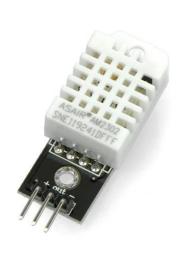


	name	surname	address
0	Kevin	McCallistera	Chicago, IL

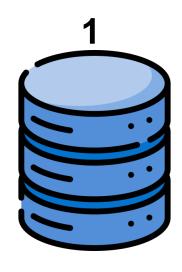
	ا	name	surname	address
(0	Kevin	McCallistera	671 Lincoln Avenue, Chicago, IL 60614



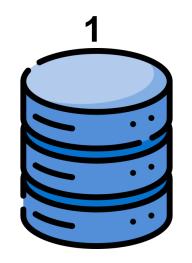


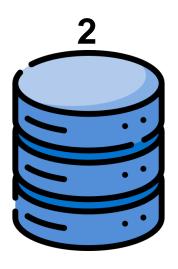


 $m 1 \pm 0.5^{\circ}C$



	name	surname		address
0	Kevin	McCallistera	671 Lincoln Avenue,	Chicago





	name	surname		address
0	Kevin	McCallistera	671 Lincoln Avenue,	Chicago

	name	surname		address
0	Kevin	McCallistera	352 Lincoln Avenue,	Chicago



	name	surname	age
0	Kevin	McCallistera	13



	name	surname	age	marital_status
0	Kevin	McCallistera	13	divorced

Completeness

	price (PLN)	country	vintage	volume (liters)	kind	medals	wegan	natural	punctation
0	49.0	Argentyna	2021.0	0.75	NaN	NaN	False	False	NaN
1	75.0	Węgry	2019.0	0.75	NaN	NaN	False	False	NaN
2	99.0	Hiszpania	2018.0	0.75	NaN	NaN	False	True	NaN
3	1163.0	Francja	2019.0	0.75	NaN	NaN	False	False	NaN
4	128.0	USA	2018.0	0.75	NaN	NaN	True	False	NaN

Presentation Quality

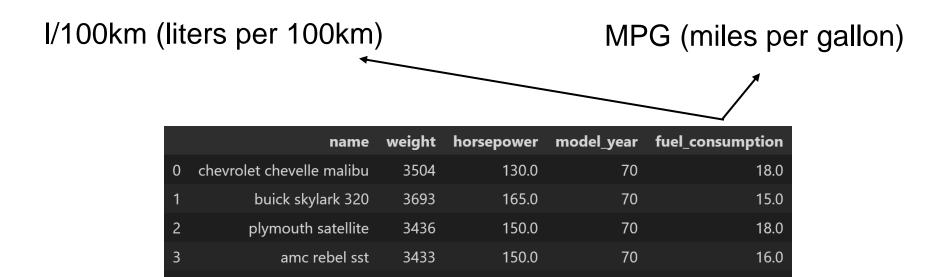
Readability

	name	weight	horsepower	model_year	col5
0	chevrolet chevelle malibu	3504	130.0	70	18.0
1	buick skylark 320	3693	165.0	70	15.0
2	plymouth satellite	3436	150.0	70	18.0
3	amc rebel sst	3433	150.0	70	16.0
4	ford torino	3449	140.0	70	17.0

Readability

	name	weight	horsepower	model_year	fuel_consumption
0	chevrolet chevelle malibu	3504	130.0	70	18.0
1	buick skylark 320	3693	165.0	70	15.0
2	plymouth satellite	3436	150.0	70	18.0
3	amc rebel sst	3433	150.0	70	16.0
4	ford torino	3449	140.0	70	17.0

Readability



140.0

70

17.0

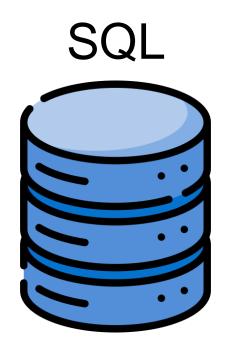
3449

ford torino

.csv, .tsv

"name", "surname", "email"
"Herminia", "Marshall", "herminia.marshall@example.com"
"Bernice", "Richardson", "bernice.richardson@example.com"
"Maeleachlainn", "Albertson", "maeleachlainn.albertson@example.com"
"Laloecen", "Darwin", "laloecen.darwin@example.com"
"Shib", "Payton", "shib.payton@example.com"
"Marcos", "Bertolini", "marcos.bertolini@example.com"
"Daniël", "Teague", "daniël.teague@example.com"
"Ikaros", "Garber", "ikaros.garber@example.com"
"Regulus", "Cornell", "regulus.cornell@example.com"
"Lars", "Simen", "lars.simen@example.com"





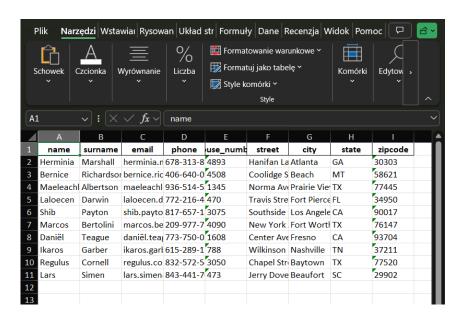


.json

```
"name":{
   "0":"Herminia",
   "1": "Bernice",
   "2": "Maeleachlainn",
   "3":"Laloecen",
   "4":"Shib",
   "5": "Marcos",
   "6":"Dani\u00ebl",
   "7":"Ikaros",
   "8":"Regulus",
   "9":"Lars"
"surname":{
   "0":"Marshall",
   "1": "Richardson",
   "2": "Albertson",
   "3":"Darwin",
   "4":"Payton",
   "5": "Bertolini",
   "6":"Teague",
```



Excel





index	feature_1	feature_2	feature_3	feature_4	feature_5	feature_6
1	1.474	-0.461	1.106	-0.559	-2.078	0.106
2	1.752	-0.688	0.21	-0.695	0.863	0.043
3	0.727	0.200	0.779	1.177	-1.702	-0.894
4	1.752	-0.688	0.21	-0.695	0.863	0.043
5	1.474	-0.461	1.106	-0.559	-2.078	0.106
6	1.752	-0.688	0.21	-0.695	0.863	0.043
7	0.727	0.200	0.779	1.177	-1.702	-0.894
8	1.474	-0.461	1.106	-0.559	-2.078	0.106
9	1.752	-0.688	0.21	-0.695	0.863	0.043
10	0.727	0.200	0.779	1.177	-1.702	-0.894
11	1.474	-0.461	1.106	-0.559	-2.078	0.106
12	1.752	-0.688	0.21	-0.695	0.863	0.043
13	0.727	0.200	0.779	1.177	-1.702	-0.894
14	0.727	0.200	0.779	1.177	-1.702	-0.894
15	1.474	-0.461	1.106	-0.559	-2.078	0.106
16	1.752	-0.688	0.21	-0.695	0.863	0.043

.pdf



index	feature_1	feature 2	feature_3	feature_4	feature_5	feature_6
1	1,474	-0.461	1.106	-0.559	-2.078	0.106
2	1.752	-0.688	0.21	-0.695	0.863	0.043
3	0.727	0.200	0.779	1.177	-1.702	-0.894
4	1.752	-0.688	0.21	-0.695	0.863	0.043
5	1.474	-0.461	1.106	-0.559	-2.078	0.106
6	1.752	-0.688	0.21	-0.695	0.863	0.043
7	0.727	0.200	0.779	1.177	-1.702	-0.894
8	1.474	-0.461	1.106	-0.559	-2.078	0.106
9	1.752	-0.688	0.21	-0.695	0.863	0.043
10	0.727	0.200	0.779	1.177	-1.702	-0.894
11	1,474	-0.461	1.106	-0.559	-2.078	0.106
12	1.752	-0.688	0.21	-0.695	0.863	0.043
13	0.727	0.200	0.779	1.177	-1.702	-0.894
14	0.727	0.200	0.779	1.177	-1.702	-0.894
15	1.474	-0.461	1.106	-0.559	-2.078	0.106
16	1.752	-0.688	0.21	-0.695	0.863	0.043

.pdf

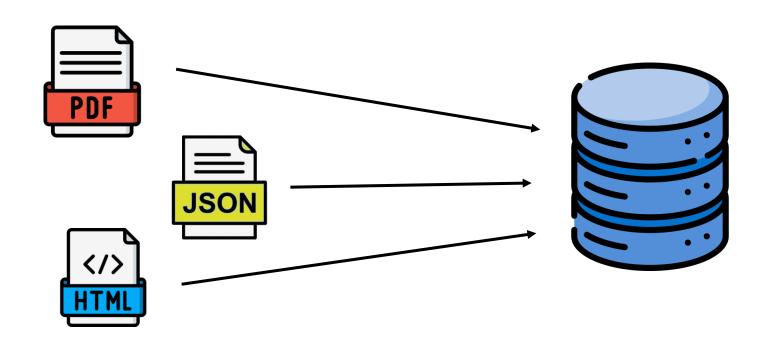


G G			feature_2	feature 3	feature 4	feature 5	feature 6
	index	feature_1	-0.461	1,106	-0.559	-2.078	0.106
	- 1	1.752	-0.688	0.21	-0.695	0.863	0.043
	3	0.727	0.200	0.779	1,177	-1,702	-0.894
	4	1.752	-0.688	0.21	-0.695	0.863	0.043
-	5	1.474	-0.461	1.106	-0.559	-2.078	0.106
	6	1.752	-0.688	0.21	-0.695	0.863	0.043
	7	0.727	0.200	0.779	1.177	-1.702	-0.894
	8	1.474	-0.461	1.106	+0.559	-2,078	0.106
	9	1.752	-0.688	0.21	-0.695	0.863	0.043
	10	0.727	0.200	0.779	1.177	-1.702	-0.894
	-11	1,474	-0.461	1.106	-0.559	-2:078	0.106
	12	1.752	-0.688			0.863	0.043
	13	0.727	0.200		1,177	-15702	-0.894
	14	0.727	0.200	0.779	1.177	-1.702	-0.894
	15	1.474	-0.461	1.106	-0.559	-2.078	
	16	1.752	-0.688		-0.695	0.863	0.043
		A SHEET HER	Market Street		A Audio		
			1.00				
	CHE THE						
	CONT.						



Data cleaning

From unstructured data to structured data



Removing irrelevant data

	name	weight (lbs)	horsepower	model_year	mpg	link
0	toyota corona	2702	96.0	75	24.0	https://pl.wikipedia.org/wiki/Toyota_Corona
1	chevrolet monte carlo s	4082	145.0	73	15.0	https://pl.wikipedia.org/wiki/Chevrolet_Monte
2	opel manta	2158	75.0	73	24.0	https://pl.wikipedia.org/wiki/Opel_Manta
3	honda civic 1500 gl	1850	NaN	80	44.6	https://pl.wikipedia.org/wiki/Honda_Civic
4	chevrolet vega	2401	72.0	73	21.0	https://pl.wikipedia.org/wiki/Chevrolet_Vega
5	chevrolet vega	2408	90.0	72	20.0	https://pl.wikipedia.org/wiki/Chevrolet_Vega

Removing irrelevant data

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	75	24.0
1	chevrolet monte carlo s	4082	145.0	73	15.0
2	opel manta	2158	75.0	73	24.0
3	honda civic 1500 gl	1850	NaN	80	44.6
4	chevrolet vega	2401	72.0	73	21.0
5	chevrolet vega	2408	90.0	72	20.0

Removing duplicates

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	75	24.0
1	chevrolet monte carlo s	4082	145.0	73	15.0
2	opel manta	2158	75.0	73	24.0
3	honda civic 1500 gl	1850	NaN	80	44.6
4	chevrolet vega	2401	72.0	73	21.0
5	chevrolet vega	2408	90.0	72	20.0

Removing duplicates

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	75	24.0
1	chevrolet monte carlo s	4082	145.0	73	15.0
2	opel manta	2158	75.0	73	24.0
3	honda civic 1500 gl	1850	NaN	80	44.6
4	chevrolet vega	2401	72.0	73	21.0
5	chevrolet vega	2408	90.0	72	20.0

Removing duplicates

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	75	24.0
1	chevrolet monte carlo s	4082	145.0	73	15.0
2	opel manta	2158	75.0	73	24.0
3	honda civic 1500 gl	1850	NaN	80	44.6
4	chevrolet vega	2401	72.0	73	21.0

Type conversions

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	75	24.0
1	chevrolet monte carlo s	4082	145.0	73	15.0
2	opel manta	2158	75.0	73	24.0
3	honda civic 1500 gl	1850	NaN	80	44.6
4	chevrolet vega	2401	72.0	73	21.0

numpy.int64

Type conversions

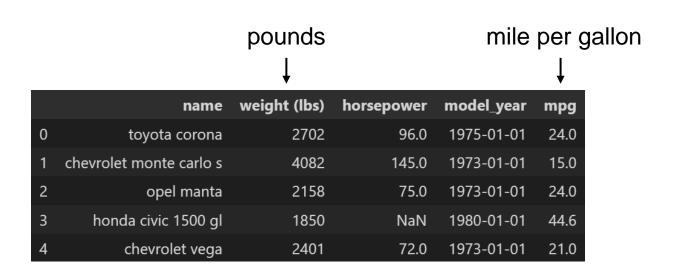
	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	1975-01-01	24.0
1	chevrolet monte carlo s	4082	145.0	1973-01-01	15.0
2	opel manta	2158	75.0	1973-01-01	24.0
3	honda civic 1500 gl	1850	NaN	1980-01-01	44.6
4	chevrolet vega	2401	72.0	1973-01-01	21.0

pandas._libs.tslibs.timestamps.Timestamp

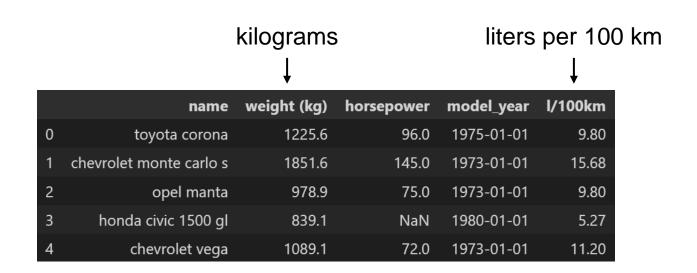
Units conversion

	name	weight (lbs)	horsepower	model_year	mpg
0	toyota corona	2702	96.0	1975-01-01	24.0
1	chevrolet monte carlo s	4082	145.0	1973-01-01	15.0
2	opel manta	2158	75.0	1973-01-01	24.0
3	honda civic 1500 gl	1850	NaN	1980-01-01	44.6
4	chevrolet vega	2401	72.0	1973-01-01	21.0

Units conversion



Units conversion



	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Delete

Delete or Impute

Deleting rows

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Deleting columns

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Imputing value

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Mean

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Mean

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Mean

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	97.0	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

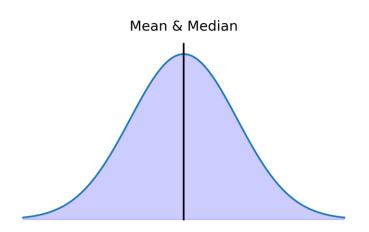
Median

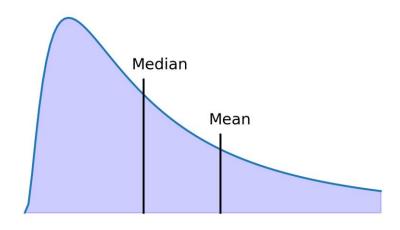
	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	NaN	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

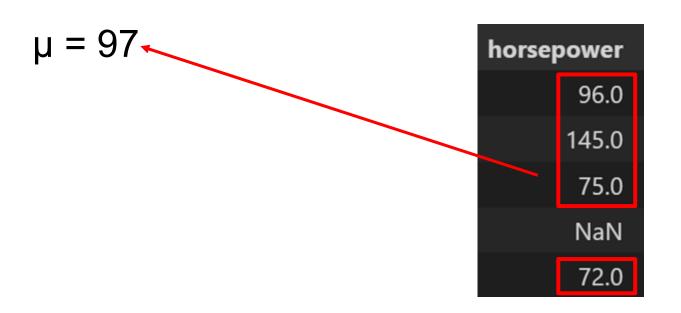
Median

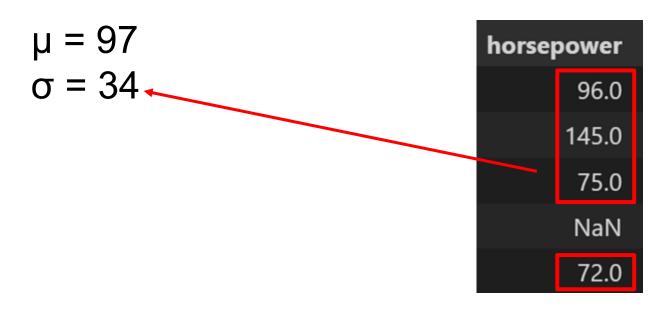
	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	85.5	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Mean vs. Median

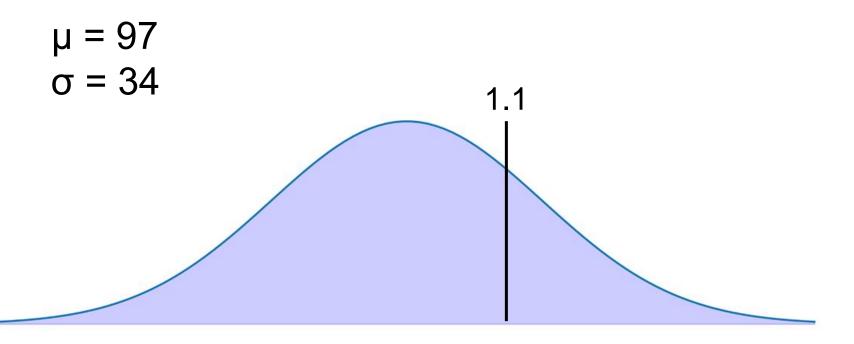








$$\mu = 97$$
 $\sigma = 34$



weight (kg)	horsepower	model_year	l/100km
1225.6	96.0	1975-01-01	9.80
1851.6	145.0	1973-01-01	15.68
978.9	75.0	1973-01-01	9.80
839.1	NaN	1980-01-01	5.27
1089.1	72.0	1973-01-01	11.20

training features

weight (kg)	horsepower	model_year	l/100km	
1225.6	96.0	1975-01-01	9.80	
1851.6	145.0	1973-01-01	15.68	
978.9	75.0	1973-01-01	9.80	
839.1	839.1 NaN 1980-01-01		5.27	
1089.1	72.0	1973-01-01	11.20	

training features training targets

weight (kg)	horsepower	model_year	l/100km	
1225.6	96.0	1975-01-01	9.80	
1851.6	145.0	1973-01-01	15.68	
978.9	75.0	1973-01-01	9.80	
839.1	839.1 NaN 198		5.27	
1089.1	72.0	1973-01-01	11.20	

training features training targets

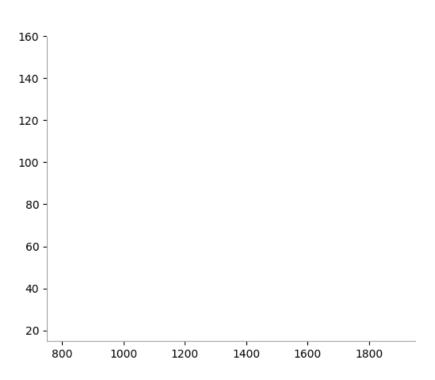
features for prediction

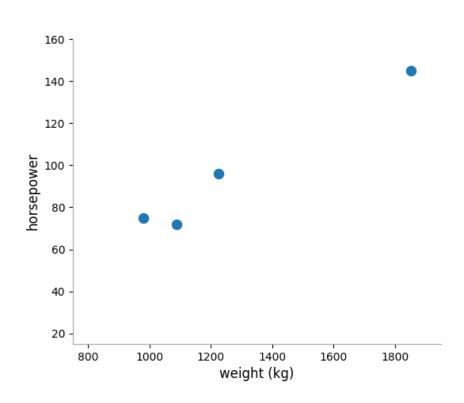
weight (kg)	horsepower	model_year	l/100km	
1225.6	96.0	1975-01-01	9.80	
1851.6	145.0	1973-01-01	15.68	
978.9	75.0	1973-01-01	9.80	
839.1	NaN	1980-01-01	5.27	
1089.1	72.0	1973-01-01	11.20	

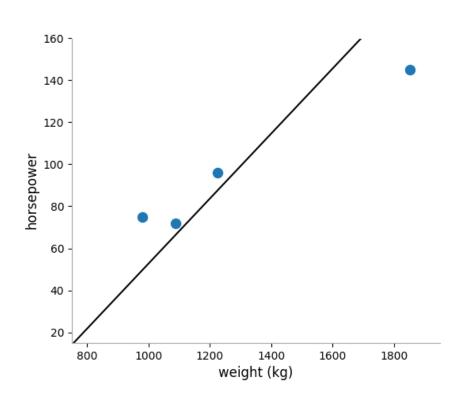
training features training targets

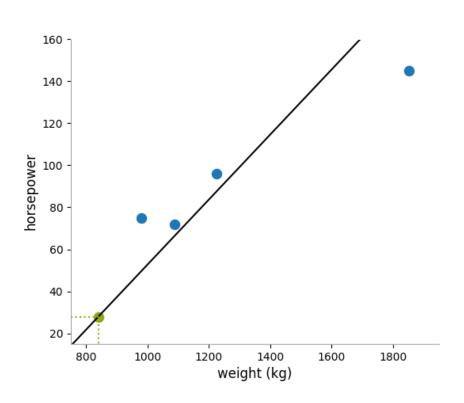
features for prediction missing values

weight (kg)	horsepower	model_year	l/100km	
1225.6	96.0	1975-01-01	9.80	
1851.6	145.0	1973-01-01	15.68	
978.9	75.0	1973-01-01	9.80	
839.1	NaN	1980-01-01	5.27	
1089.1	72.0	1973-01-01	11.20	









	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	27.9	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

Flags

	name	weight (kg)	horsepower	model_year	l/100km
0	toyota corona	1225.6	96.0	1975-01-01	9.80
1	chevrolet monte carlo s	1851.6	145.0	1973-01-01	15.68
2	opel manta	978.9	75.0	1973-01-01	9.80
3	honda civic 1500 gl	839.1	missing	1980-01-01	5.27
4	chevrolet vega	1089.1	72.0	1973-01-01	11.20

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