Sports and Performance Science Portfolio

Christian Monteferrante, MSc., CSCS

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- Project 1: Volleyball anual report – National University of La Matanza
  - Tools: Excell, Powerpoint, Jamovi (R)
  - Dataset: Real volleyball data

- Project 2: Edith Cowan University – Master of Exercise Science
  - Tools: Excel, Visual Basic
  - Dataset: ECU – Monitoring unit assignment

- Project 3: Big Data – Data Science course
  - Tools: Google Sheets, Google Looker Studio, Python, Deep Note
  - Datasets: “Services”, “Internet”, “Exams”

Project 1: University of La Matanza 2023

Anual Report

Volleyball D1 – Femenine

Christian Monteferrante, MSc., CSCS

Universidad Nacional de La Matanza

Personal Report

Excel

Powerpoint

Personal Report

1RM Estimated from Multiple Max Repetitions (xRM) - April to November 2023

Player

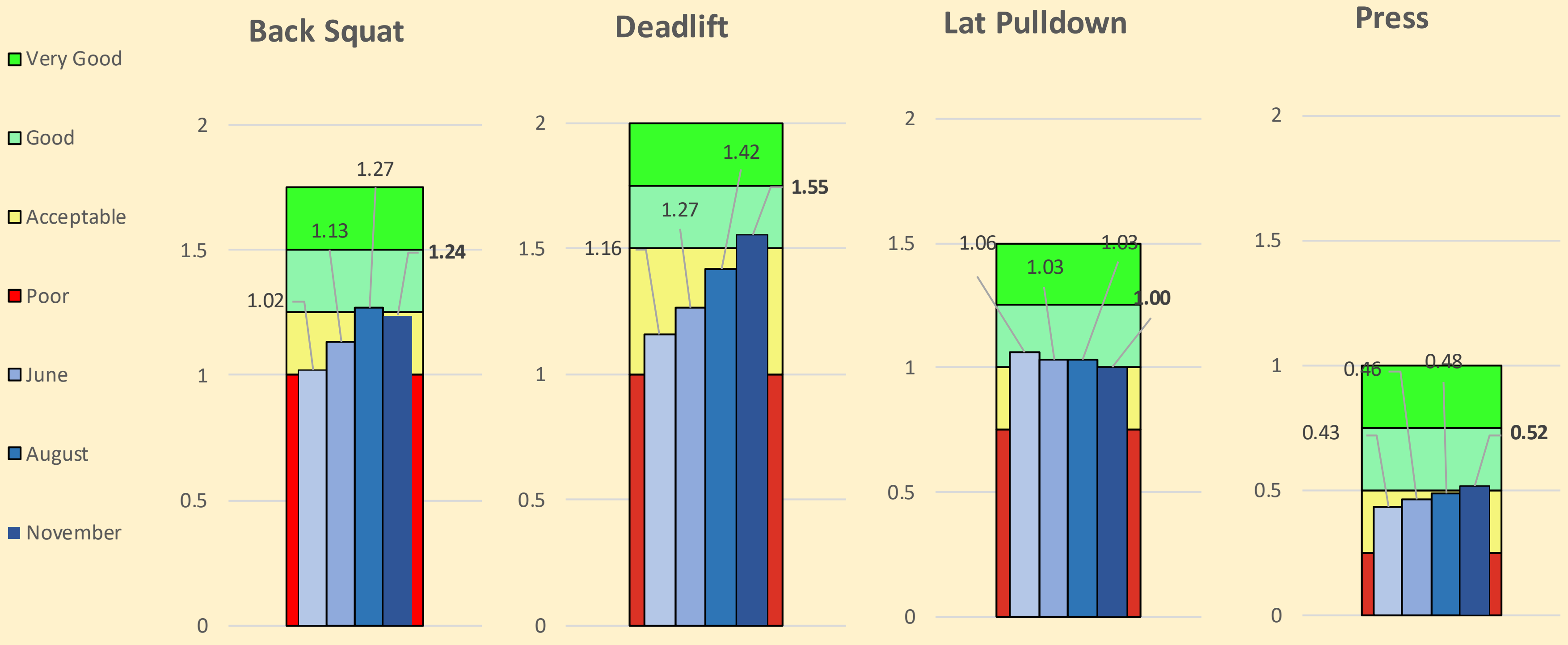
Assistance
92%

Bodyweight
66.7 kg -0.80

Absolute Values for Estimated 1RM

Back Squat	Deadlift	Lat Pulldown	Press
82.7 Kg -2.9	**103.6 Kg** 7.9	**66.7 Kg** -3.1	**34.4 Kg** 1.8
		Pull Ups: **0.00**	

Relative to Bodyweight Values



The relative index referes to the relation between bodyweight (bw) and weight lifted. An index of 1 indicates 100% bw, 1.5, 150%bw

If any value is equal to 0, it means that the exercise was not tested

The last test was performed at the end of the Metropolitan Tournament and it corresponded to a maintenance phase

Backroom

Noviembre 2023

				Fuerza							
		Sent		Tiron		Despegue		Press			
Atleta	PC kg	S 1RM	S rel	TP 1RM	TP rel	D 1RM	D rel	P 1RM	P rel	Dominada	Asistencia
C	60.2				0.00				0.00	no	77%
C	66.7	82.7	1.24	66.7	1.00	103.6	1.55	34.4	0.52	si	92%
D	69.9	88.0	1.26	76	1.09	111.6	1.60	36.4	0.52	si	99%
G	72	91.9	1.28	55.6	0.77	90	1.25	34.0	0.47	no	76%
L	61.3		0.00		0.00		0.00		0.00		78%
L	64.4	81.5	1.27	74.9	1.16	87.9	1.36	36.1	0.56	si	91%
N	59.1	71.0	1.20	59.8	1.01	88	1.49	31.3	0.53	no	98%
R	61.3	83.3	1.36	64.5	1.05	92.4	1.51	30.1	0.49	si	86%
S	61.2	100.6	1.64	79.8	1.30	98.3	1.61	40.0	0.65	si	97%
S	89	103.5	1.16	73.7	0.83	151.8	1.71	39.2	0.44	no	88%
V	79.5	104.4	1.31	81.4	1.02	132.7	1.67	40.0	0.50	no	94%
F	72.5	98.9	1.36	84.3	1.16	111.1	1.53	40.0	0.55	si	87%
V	63.9	88.4	1.38	63.9	1.00	83.3	1.30	34.9	0.55	si	
N	79.5	103.3	1.30	77.8	0.98	105.3	1.32	33.3	0.42	no	90%

Team Evolution

jamovi

Stats.
Open.
Now.

R Programming

jamovi - FuerzaNoviembre2023-paraJamovi

Variables | Data | Analyses | Edit

Exploration | T-Tests | ANOVA | Regression | Frequencies | Factor | esci | Flexplot | Base R | R | Modules

	Equipo	Fecha	Atleta	PC kg	Sent 1RM	Sent rel	Tir
1	UNLaM	Abril 2023	Camila Mann...	55.0			
2	UNLaM	Abril 2023	Camila Palczi...	69.2	70.7	1.02	
3	UNLaM	Abril 2023	Dana Kokil	74.0	90.7	1.23	
4	UNLaM	Abril 2023	Guadalupe Di...	68.5	78.8	1.15	
5	UNLaM	Abril 2023	Lorena Reinoso	59.4	80.0	1.35	
6	UNLaM	Abril 2023	Luana Alfonso	64.2	65.2	1.02	
7	UNLaM	Abril 2023	Milagros Jacue	56.9			
8	UNLaM	Abril 2023	Rocio Brandan	61.4	69.8	1.14	
9	UNLaM	Abril 2023	Sabrina Torino	63.7	90.4	1.42	
10	UNLaM	Abril 2023	Sara Agüero	100.0	77.9	0.78	
11	UNLaM	Abril 2023	Sheila Miguel	88.2	106.6	1.21	
12	UNLaM	Abril 2023	Florencia Diaz	71.5	77.9	1.09	
13	UNLaM	Abril 2023	Valentina Noya	60.9	78.3	1.29	
14	UNLaM	Abril 2023	Vanina Nieva	77.8	91.8	1.18	
15	UNLaM	Abril 2023	Martina Fojo	76.2			
16	UNLaM	Junio 2023	Camila Mann...	58.0			
17	UNLaM	Junio 2023	Camila Palczi...	67.5	76.6	1.13	
18	UNLaM	Junio 2023	Dana Kokil	71.5	87.4	1.22	
19	UNLaM	Junio 2023	Guadalupe Di...	68.9	75.6	1.10	
20	UNLaM	Junio 2023	Lorena Reinoso	59.4			
21	UNLaM	Junio 2023	Luana Alfonso	64.5			
22	UNLaM	Junio 2023	Milagros Jacue	57.5	66.3	1.15	
23	UNLaM	Junio 2023	Rocio Brandan	61.9	84.5	1.37	
24	UNLaM	Junio 2023	Sabrina Torino	61.5	90.4	1.47	
25	UNLaM	Junio 2023	Sheila Miguel	89.0	110.8	1.24	
26	UNLaM	Junio 2023	Florencia Diaz	79.9	105.6	1.32	
27	UNLaM	Junio 2023	Valentina Noya	72.4	91.5	1.26	
28	UNLaM	Junio 2023	Vanina Nieva	60.7	78.3	1.29	

Ready Filters 0 Row count 57 Filtered 0 Deleted 0 Added 0 Cells edited 21

Results

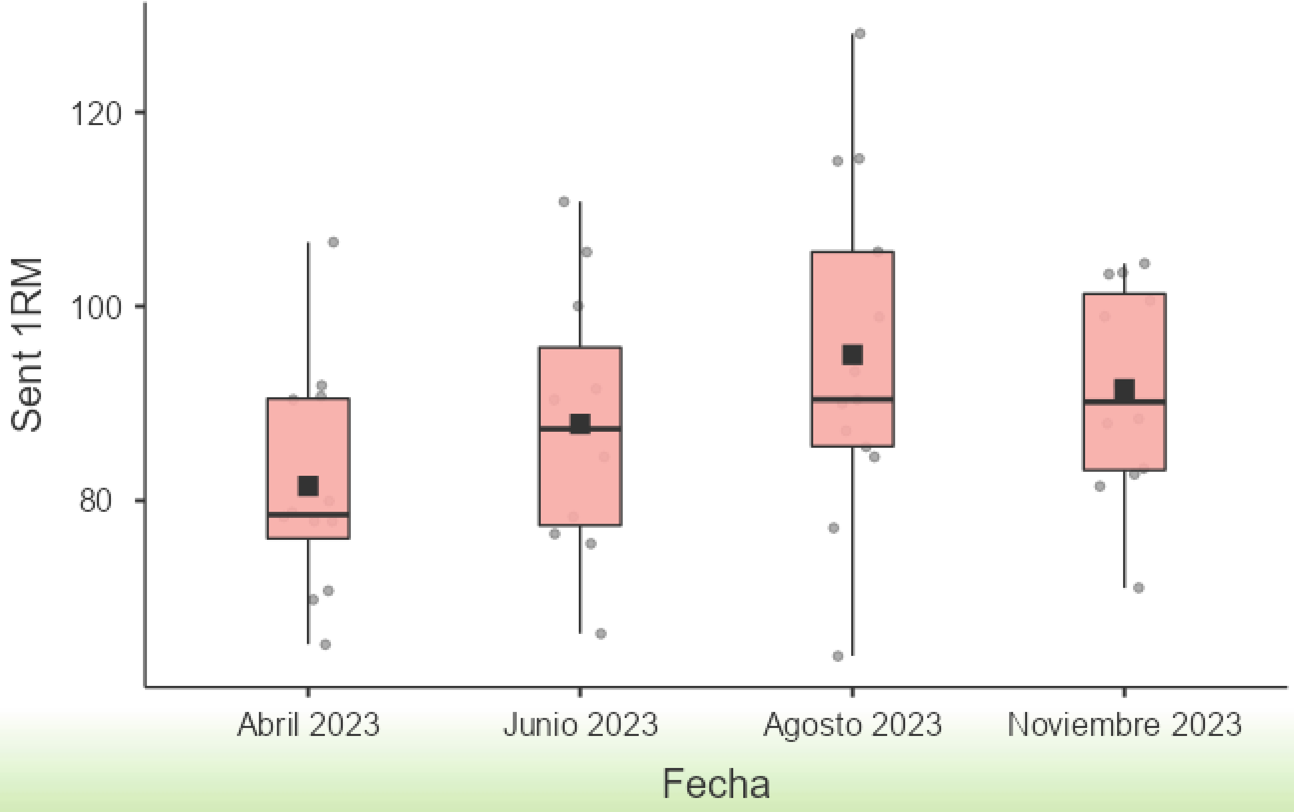
Descriptives

Descriptives

	Fecha	PC kg	Sent 1RM	Despegue 1RM	Press 1RM
N	Abril 2023	15	12	10	12
	Junio 2023	14	11	9	11
	Agosto 2023	14	13	13	14
	Noviembre 2023	14	12	12	12
Missing	Abril 2023	0	3	5	3
	Junio 2023	0	3	5	3
	Agosto 2023	0	1	1	0
	Noviembre 2023	0	2	2	2
Mean	Abril 2023	69.8	81.5	90.4	30.1
	Junio 2023	67.9	87.9	101	32.8
	Agosto 2023	67.9	95.0	106	33.6
	Noviembre 2023	68.6	91.5	105	35.8
Std. error mean	Abril 2023	3.15	3.33	6.00	1.09
	Junio 2023	2.51	4.10	8.13	1.31
	Agosto 2023	2.51	4.82	5.59	1.33
	Noviembre 2023	2.40	3.11	5.85	0.992
95% CI mean lower bound	Abril 2023	63.6	75.0	78.7	28.0
	Junio 2023	63.0	79.9	85.1	30.2
	Agosto 2023	63.0	85.6	94.8	31.1
	Noviembre 2023	63.9	85.4	93.2	33.9
95% CI mean upper bound	Abril 2023	76.0	88.0	102	32.2
	Junio 2023	72.8	96.0	117	35.3

Squat

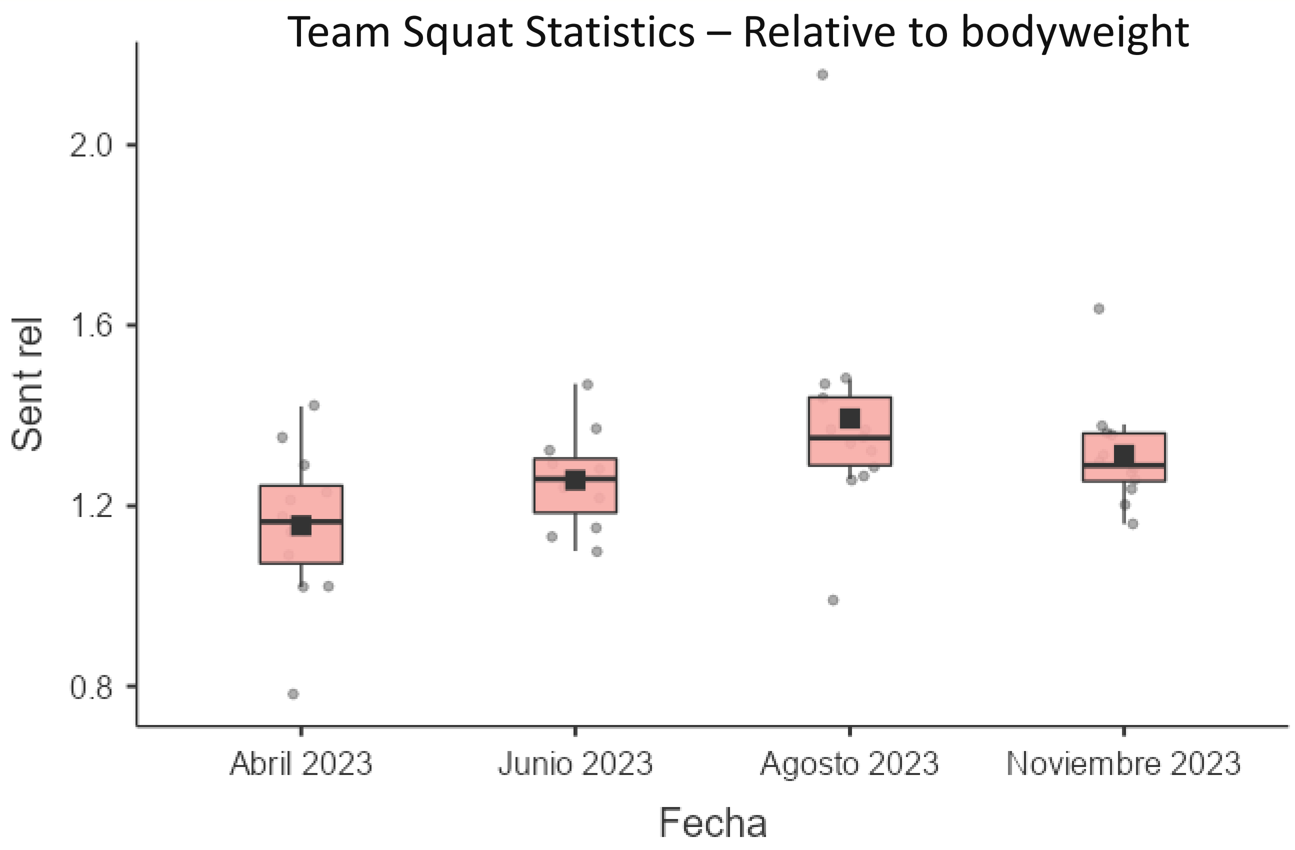
Team Squat Statistics (in kg)



The team's average squat strength increased throughout the year during the strength and power phases of the sport calendar. After the maintenance phase, which coincided with the Metropolitan Tournament, the strength level for this exercise slightly decreased within the expected parameters. However, the team finished the year with higher lower body strength compared to the beginning of the year. This places them in a more advantageous situation to tackle 2024 and the upcoming sport demands.

UNLaM

Squat



The relative strength for the squat shows a similar trend compared to the absolute values. On average, the team is better equipped to start 2024 in the category considered 'Good', which is higher than 125% of their own bodyweight, compared to April 2023 when their values were 'Acceptable', or between 100% and 125% of their own weight.

Project 2: Edith Cowan University

Edith Cowan University

Monitoring Unit (Dr. Greg Haff) - 2021

Excel

Visual Basic

Home Screen – Quick accesses

Data Imput

- Training
- Physical
- Wellness
- Match
- Medical
- Updates

Dashboards

- Individuals
- Weekly
- Team

Print Reports

- Physical
- Training
- Games
- Wellness & Medical

Databases

- Training
- Physical
- Wellness
- Match
- Medical
- Updates
- C-Pannel

Data Input Tab: Training information

Daily Training Questionnaire

Training

Date (dd-mm-yyyy)	
Name	Kendall
Training Type	Endurance
Duration (minutes)	78
Session RPE	sRPE 1 2 3 4 5 6 7 8 9 10

1 - "aint notin' but a peanut" ; 10 - "completely extenuating"

Home

Upload

Controls for Dr. H:

Database

Hide Columns

Individual Dashboard

Performance Profile: French

Controls

Select athlete to visualize data:

French

Home

French

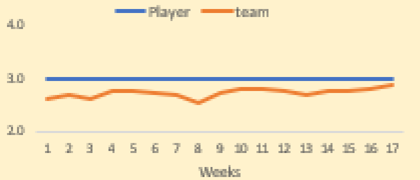
Medical

Illness Count	Injury Count	Other Medical Categories
0	0	0

Overall Availability Average

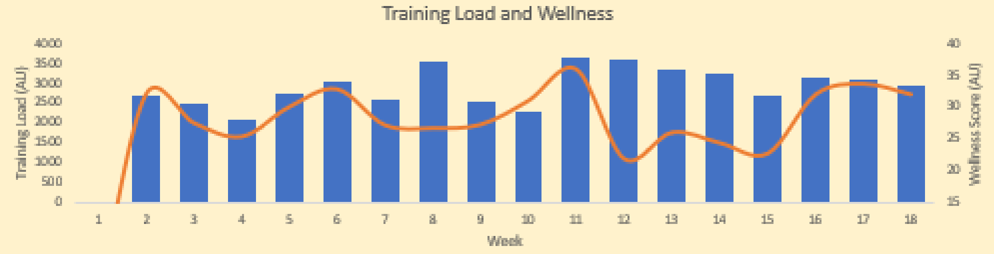
Player	3.0
Team	2.7

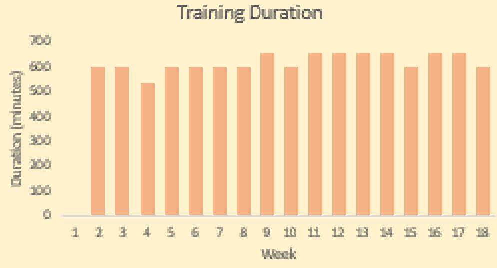
Weekly Average Availability

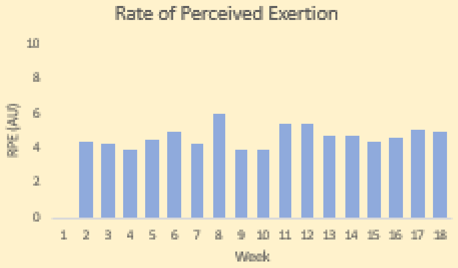


Wellness

	Sleep Quality	Sleep Hours	Soreness	Stress	Fatigue	Motivation	Wellness Score
Average of the last 7 days	3.0	7.7	4.7	4.7	4.7	7.5	32.2
Average of the last 30 days	3.3	8.0	4.4	4.4	4.4	5.4	29.8
Overall player average	3.0	7.0	4.6	4.6	4.6	5.1	29.0

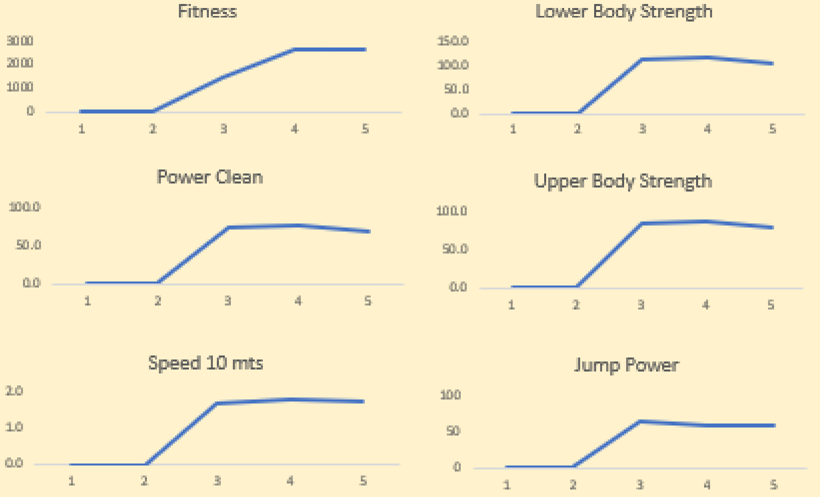






Physical

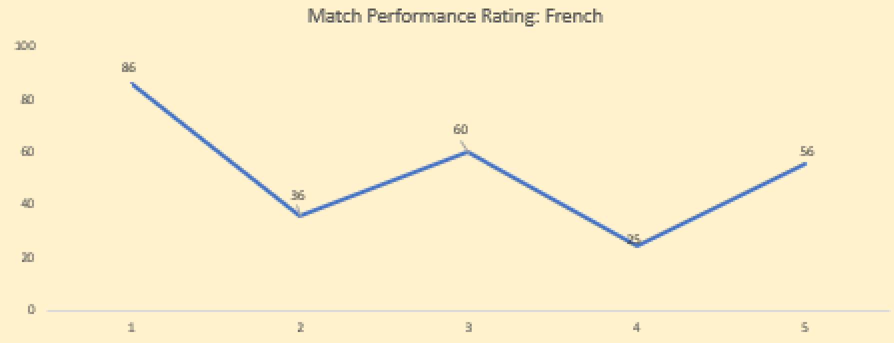
	Fitness	Lower Body Strength	Power Clean	Upper Body Strength	Speed 10 mts	Jump Power
Rating	Good	Poor	Poor	Poor	Excellent	Ok
Result	2700	105	68.25	78.75	1.75	59
Band	4	2	2	2	5	4

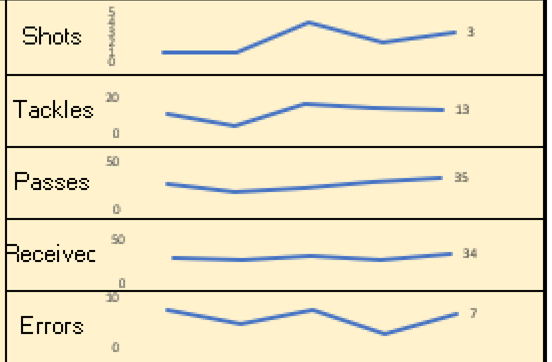


Updates

Date	Priority	Area	Comment
30/04/2022	2	Performance	Good COD technique
29/04/2022	2	Medical	Covid 19 positive
27/04/2022	2	Performance	good passes session
26/04/2022	2	Medical	Covid 19 positive
22/04/2022	2	Performance	Didn't hit tackle # goal

Match Performance





Wellness and Medical Report

Controls

Select athlete to visualize

Blitz

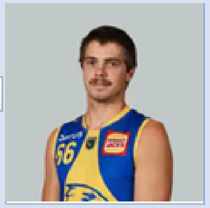
elect athlete and week to pri

1
2
3
4
5
6
7
8
9
10
11
12

Print

Home

Wellness, Medical, and Availability Report: Blitz



Total illness count
3

Total injury count
20

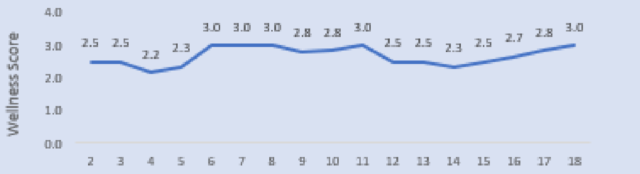
Total of other conditions count
7

	Weekly Wellness							Weekly Health			
Week	Sleep Quality	Sleep Hours	Soreness	Stress	Fatigue	Motivation	Wellness Score	Illness	Injury	Other	Availability
2	3.0	8.7	4.7	4.7	4.7	8.5	34.2	0	0	3	2.5
3	2.7	3.8	4.2	4.2	4.2	3.7	22.7	0	0	0	2.5
4	3.7	5.8	7.2	7.2	7.2	6.7	37.7	3	2	0	2.2
5	2.7	8.0	6.3	6.3	6.3	5.7	35.3	0	4	0	2.3
6	3.7	6.0	4.5	4.5	4.5	3.5	26.7	0	0	0	3.0
7	4.2	3.3	5.2	5.2	5.2	4.7	27.7	0	0	0	3.0
8	2.5	5.2	6.5	6.5	6.5	5.0	32.2	0	0	0	3.0
9	3.2	9.6	5.2	5.2	5.2	4.6	33.0	0	0	1	2.8
10	3.5	5.8	4.2	4.2	4.2	5.5	27.3	0	0	1	2.8
11	3.0	5.7	6.1	6.1	6.1	5.4	32.6	0	0	0	3.0
12	3.5	5.2	5.7	5.7	5.7	4.8	30.5	0	3	0	2.5
13	2.5	6.3	4.8	4.8	4.8	3.5	26.8	0	3	0	2.5
14	3.3	7.8	8.3	8.3	8.3	7.0	43.2	0	4	0	2.3
15	4.5	5.3	8.2	8.2	8.2	5.2	39.5	0	3	0	2.5
16	2.5	7.8	3.0	3.0	3.0	6.2	25.5	0	1	1	2.7
17	2.5	6.8	4.8	4.8	4.8	4.5	28.3	0	0	1	2.8
18	2.5	9.3	6.2	6.2	6.2	5.2	35.5	0	0	0	3.0

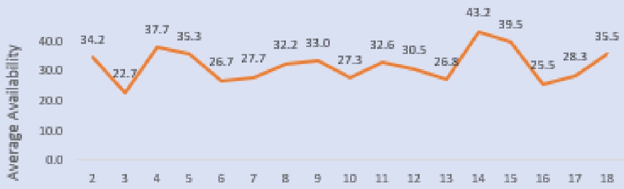
Latest Comments

Date	Priority	Area	Comment
29-04-22	1	Medical	Hip injury
28-04-22	1	Strength & Conditioning	Much lower performance than usual
26-04-22	1	Medical	Light hip pain
23-04-22	1	Strength & Conditioning	lower performance than usual
20-04-22	1	Medical	Feeling in the hip

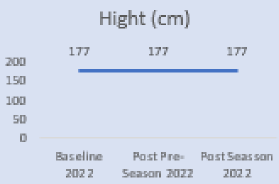
Weekly Wellness

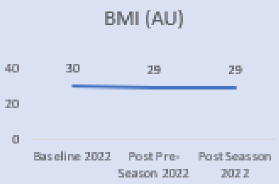


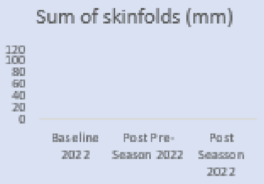
Weekly Availability



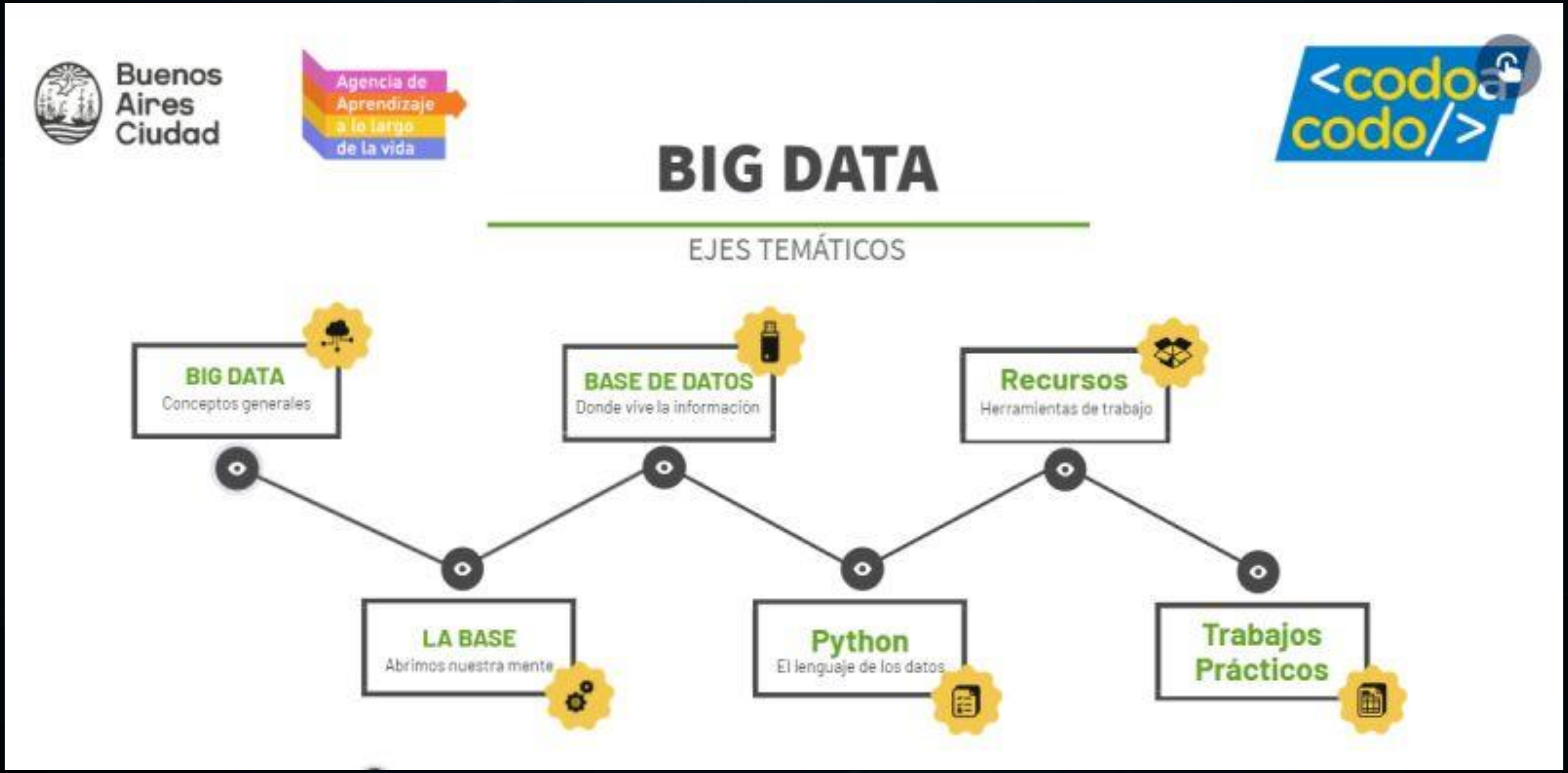
Anthropometrics



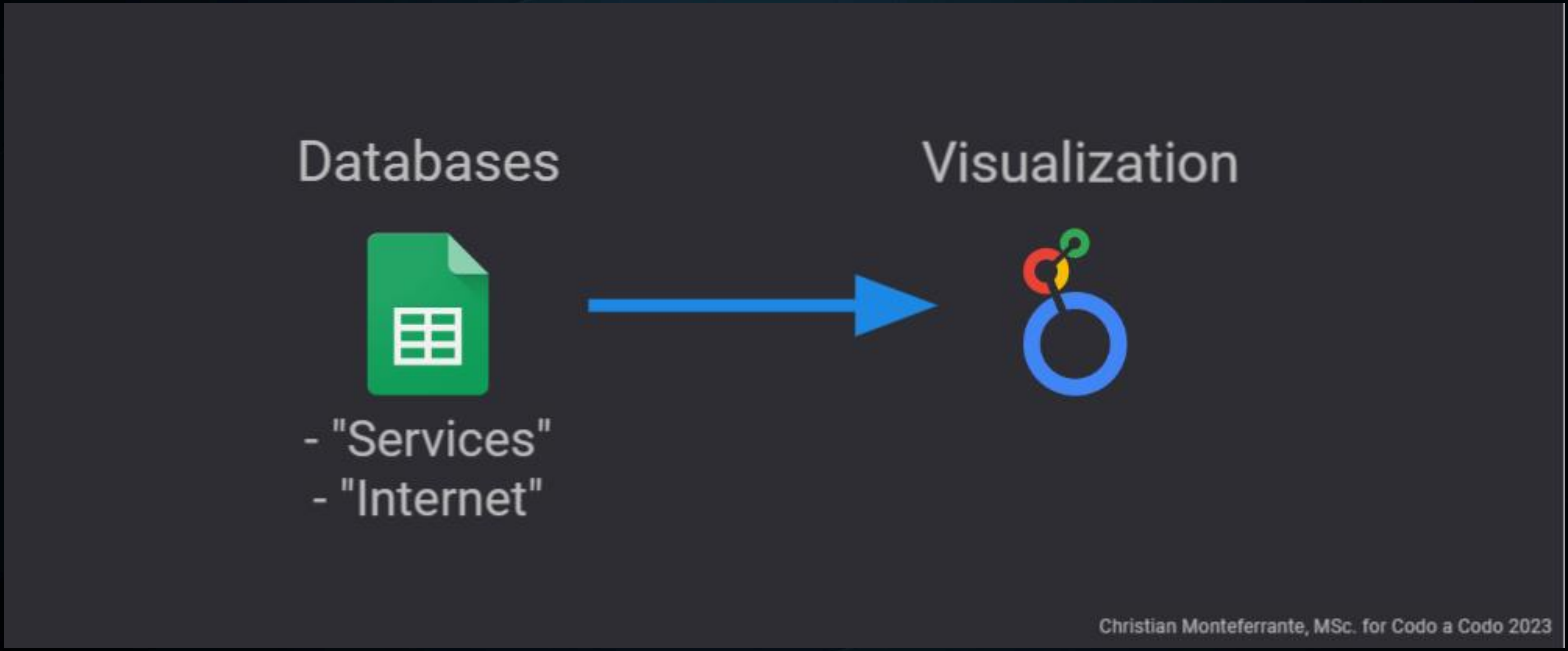




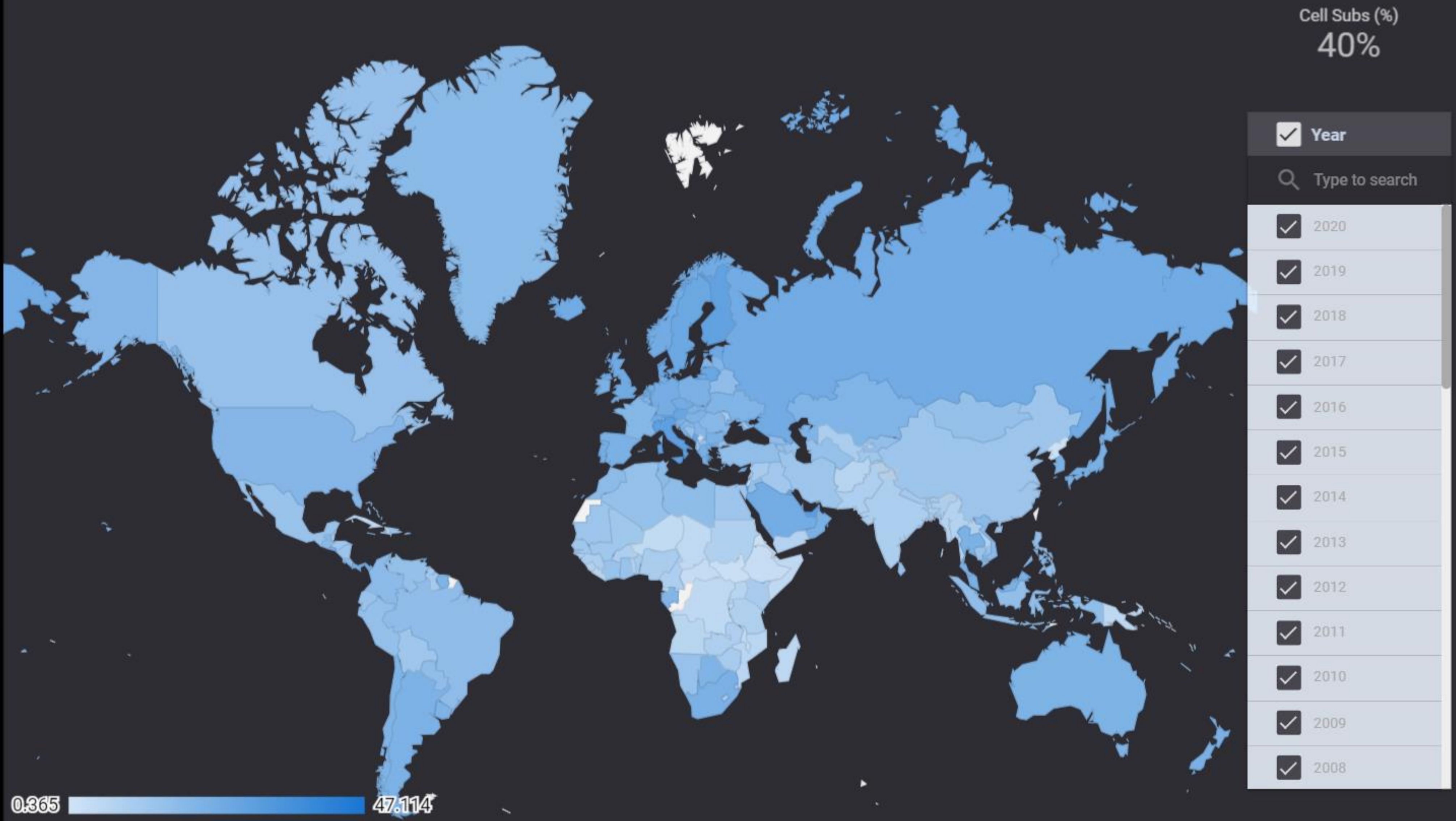
Project 3: Big Data – 2023



Sheets + Looker Studio



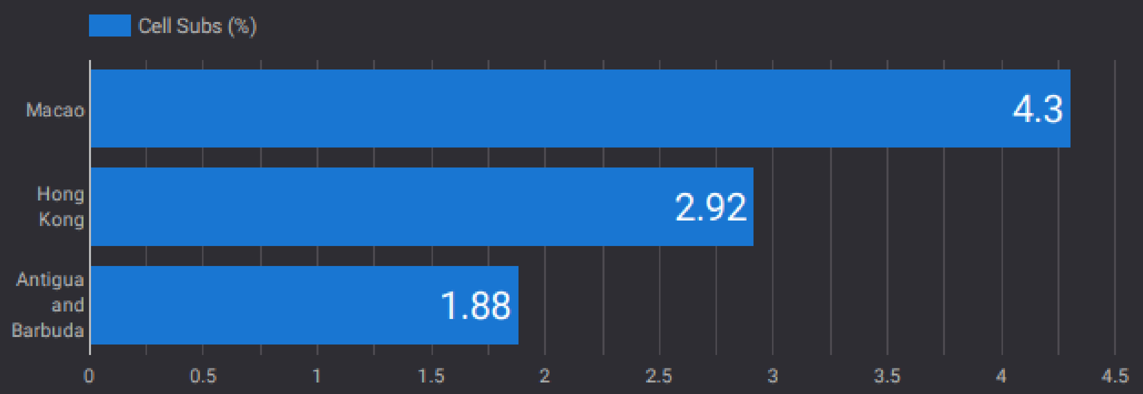
World mobile subscriptions percentage by country, from 1980 to 2020



Over 100% denotes more than one mobile subscription per person

Country with the most mobile lines per person in 2020: Macao

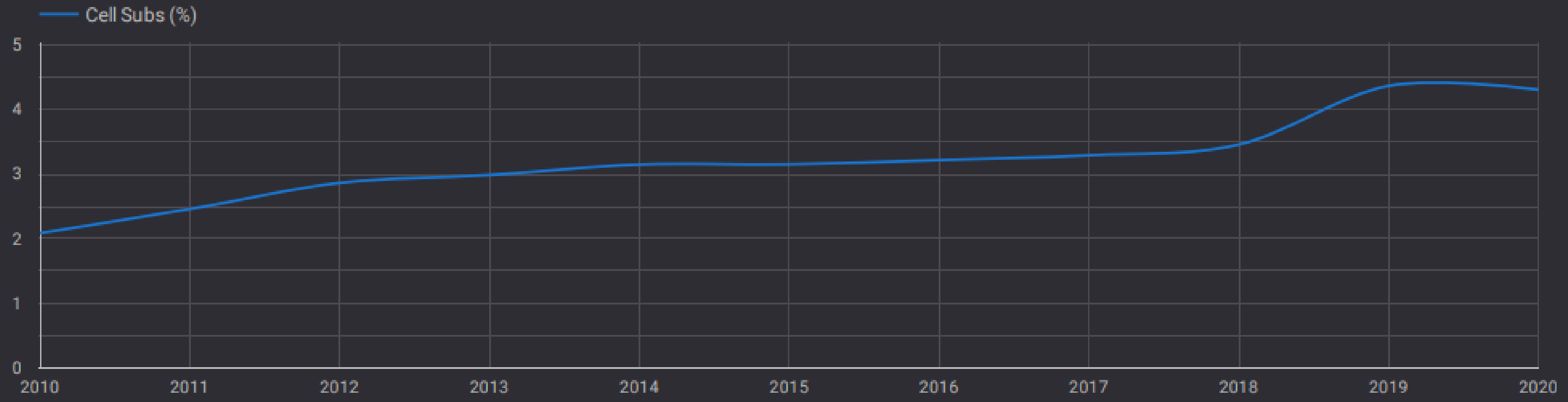
Top three countries with the most mobile lines per person



Macao's average mobile line's ownership per person:

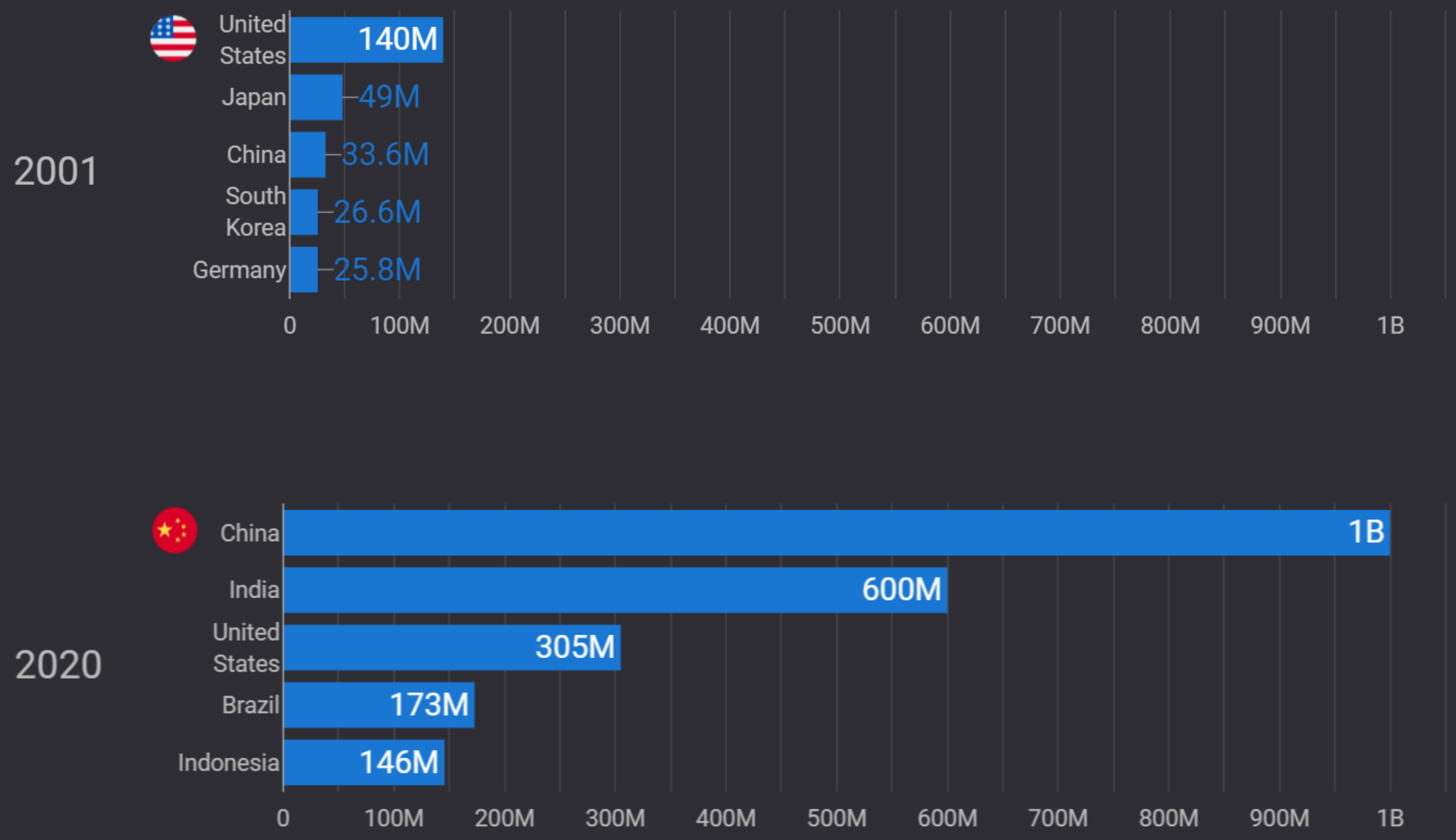
4.3

Macao's cell-phones ownership for 2010-2020



Christian Monteferrante, MSc. for Codo a Codo 2023

Top five countries with the highest number of internet users



Christian Monteferrante, MSc. for Codo a Codo 2023

Dataset: “exams”

Basic Operations

Review data types

```
df.dtypes
```

```
id                              object
gender                          object
race/ethnicity                  object
parental level of education     object
lunch                           object
employed                        object
test preparation course         object
math score                     float64
physics score                  float64
chemistry score                float64
algebra_score                  float64
dtype: object
```

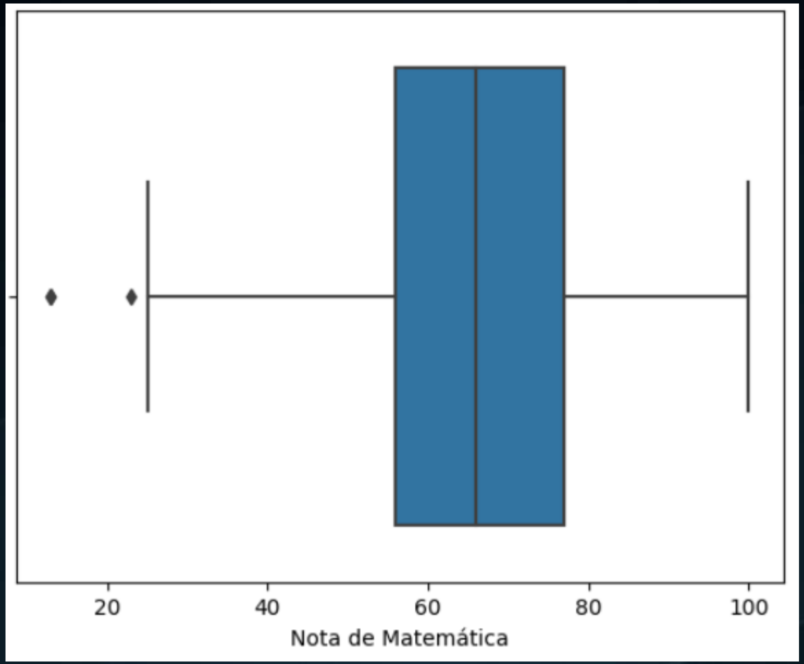
Drop duplicates

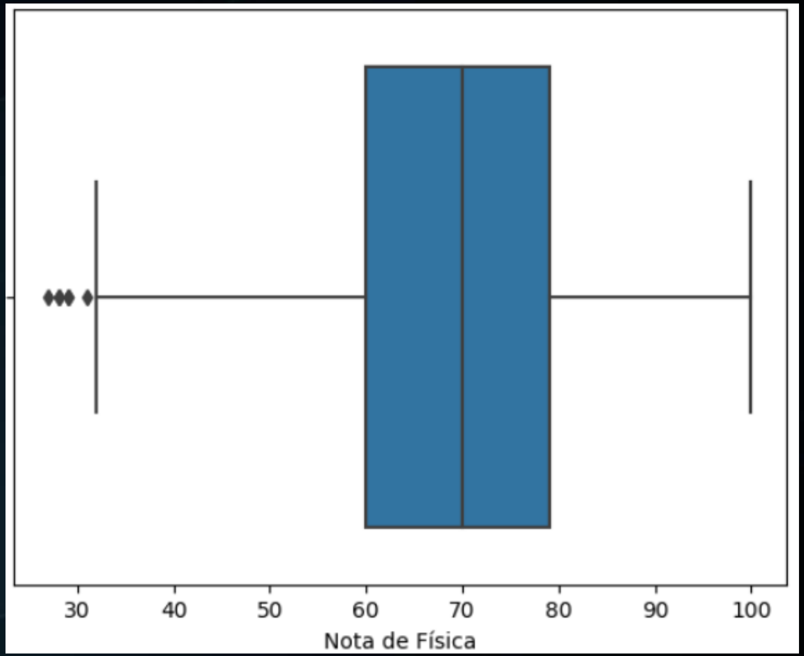
```
print(f'Original: {df.id.count()} filas')
duplicate_rows_df = df[df.duplicated()] #"duplicated???"
print(f'Cantidad de filas duplicadas: {duplicate_rows_df.id.count()}')

#eliminar duplicados
df = df.drop_duplicates()
#print (df.head())

# Filas despues de eliminar duplicados
print(f'Final: {df.id.count()} filas')

```

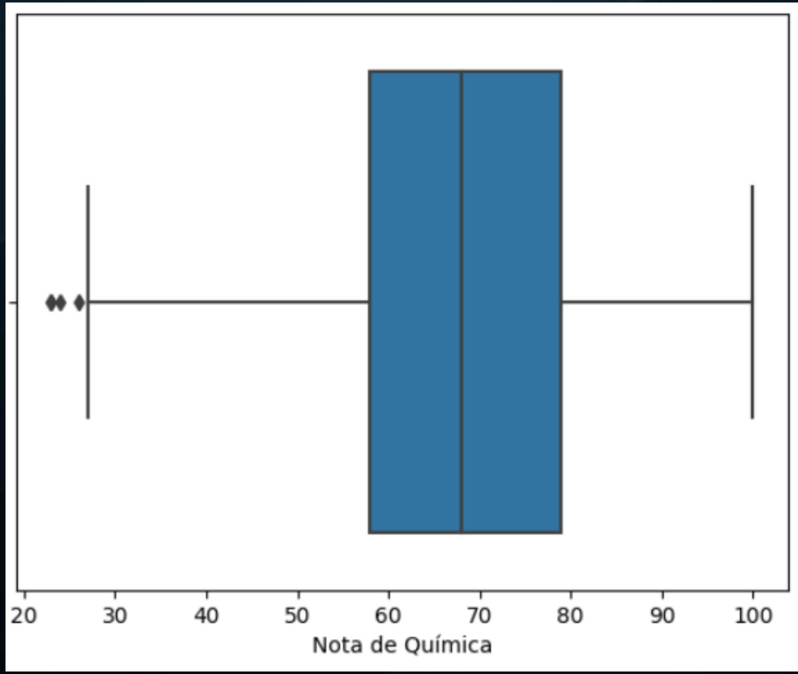
```
Original: 1018 filas
Cantidad de filas duplicadas: 18
Final: 1000 filas
```

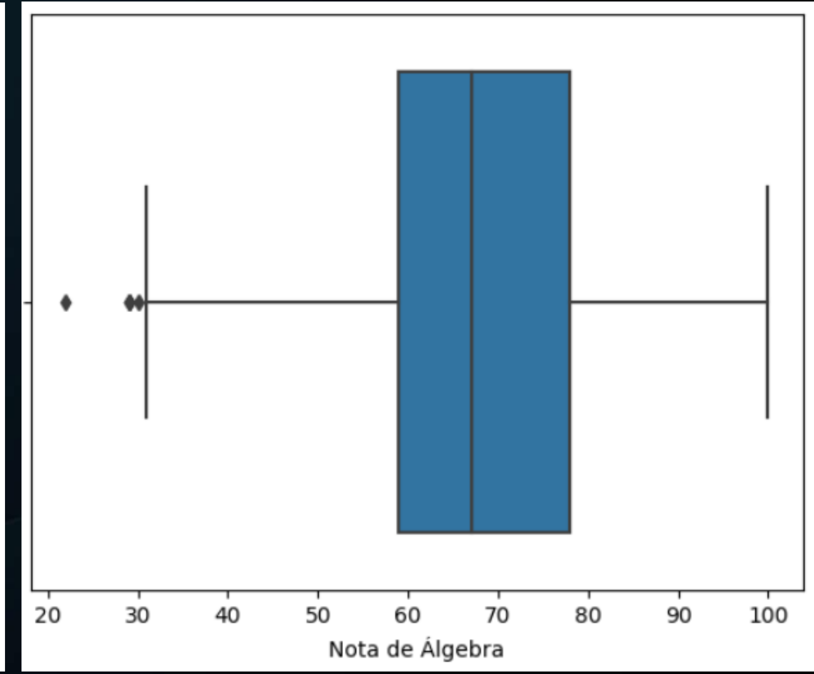
Detect outliers

```
#materias renombradas:
#"math score": "Nota de Matemática",
#"physics score": "Nota de Física",
#"chemistry score": "Nota de Química",
#"algebra_score": "Nota de Álgebra"

sns.boxplot(x=df['Nota de Matemática'])
plt.show()
sns.boxplot(x=df['Nota de Física'])
plt.show()
sns.boxplot(x=df['Nota de Química'])
plt.show()
sns.boxplot(x=df['Nota de Álgebra'])
plt.show()
```



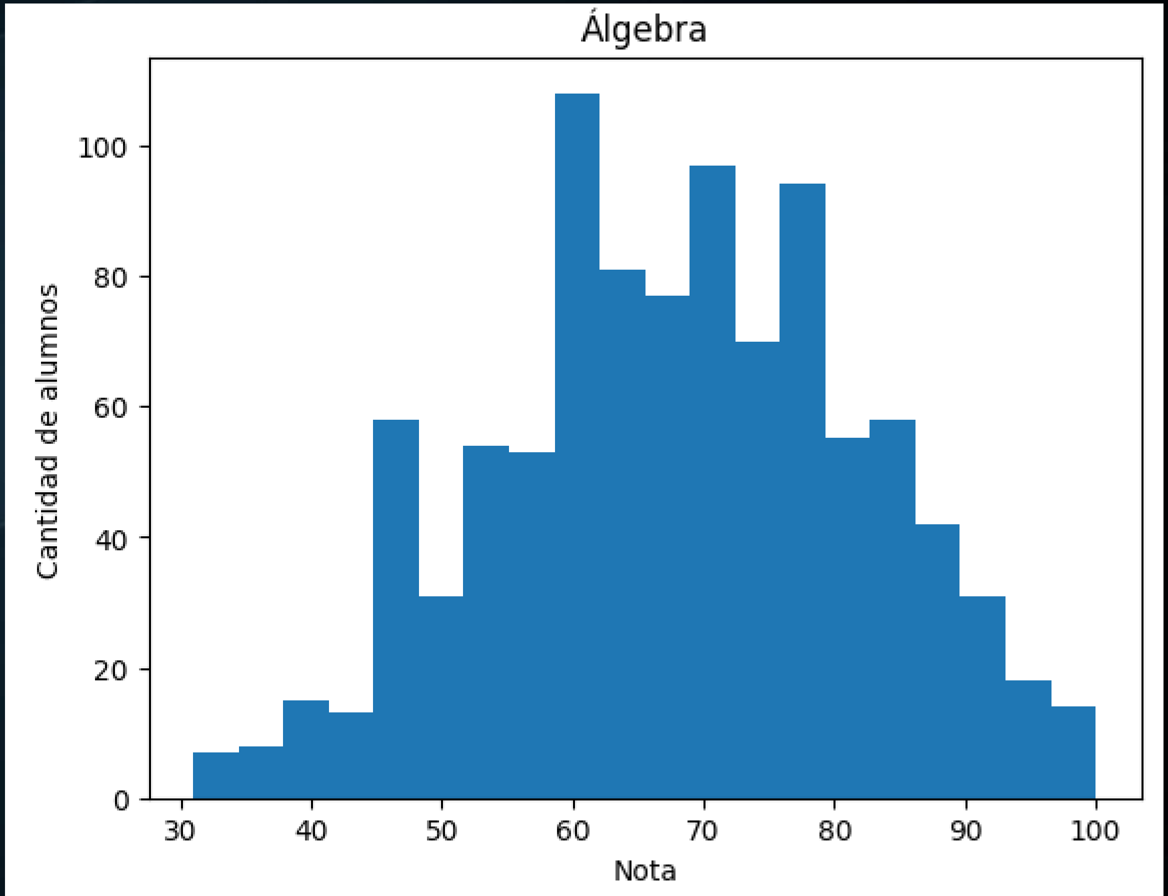






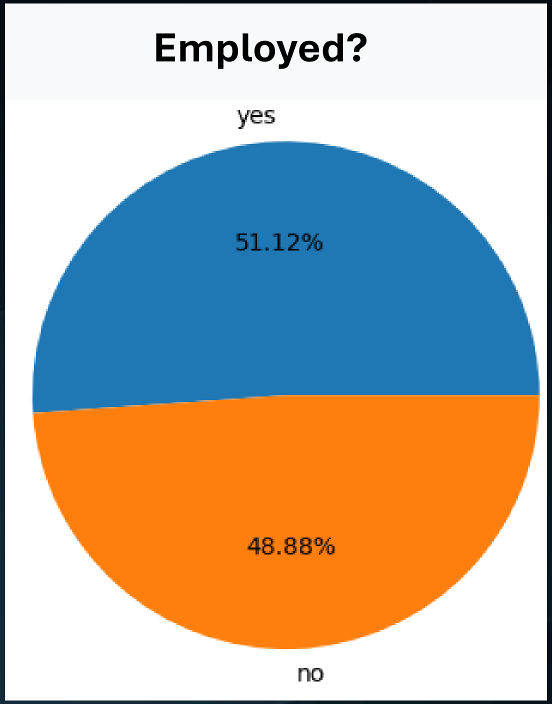
Frequencies: Plot histograms

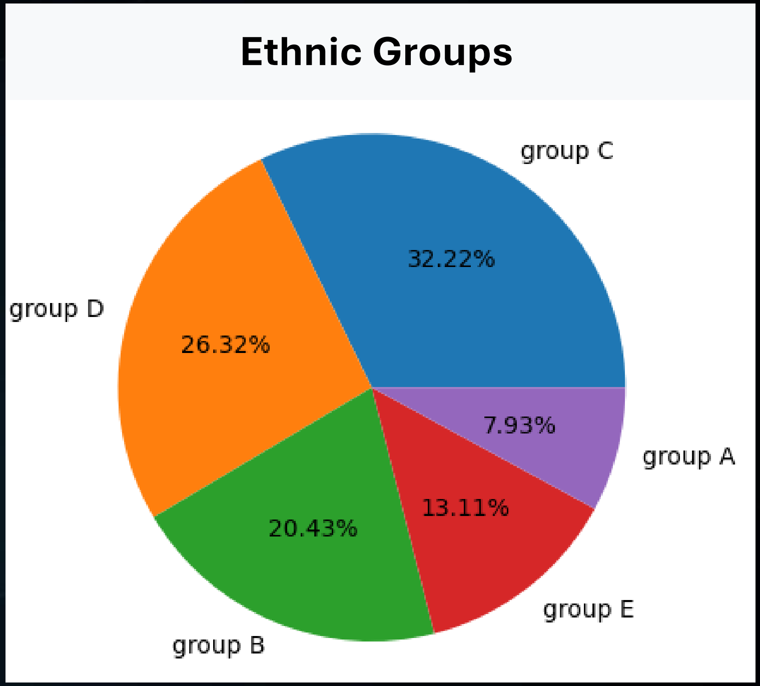
```
#"math score": "Nota de Matemática",
#"physics score": "Nota de Física",
#"chemistry score": "Nota de Química",
#"algebra_score": "Nota de Álgebra"

#Algebra
plt.hist(df['Nota de Álgebra'], bins=20)
plt.title("Álgebra")
plt.ylabel("Cantidad de alumnos")
plt.xlabel("Nota")
plt.show()

#Chemistry
plt.hist(df['Nota de Química'], bins=20)
plt.title("Química")
plt.ylabel("Cantidad de alumnos")
plt.xlabel("Nota")
plt.show()

#Math
plt.hist(df['Nota de Matemática'], bins=20)
plt.title("Matemática")
plt.ylabel("Cantidad de alumnos")
plt.xlabel("Nota")
plt.show()

#Physics
plt.hist(df['Nota de Física'], bins=20)
plt.title("Física")
plt.ylabel("Cantidad de alumnos")
plt.xlabel("Nota")
plt.show()
```

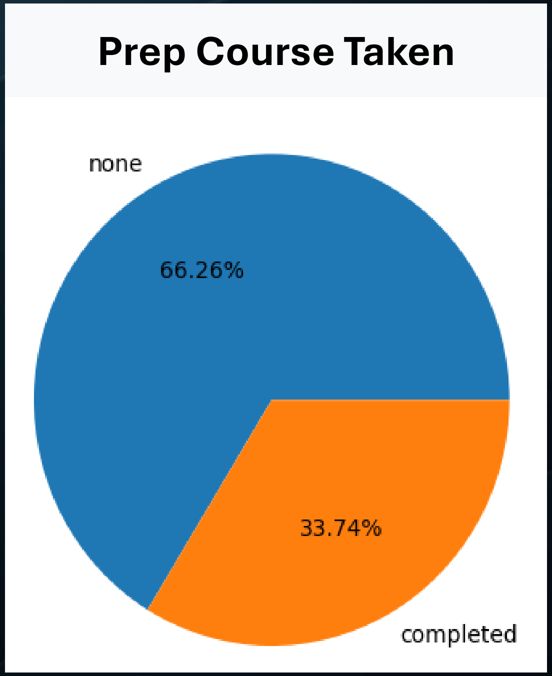


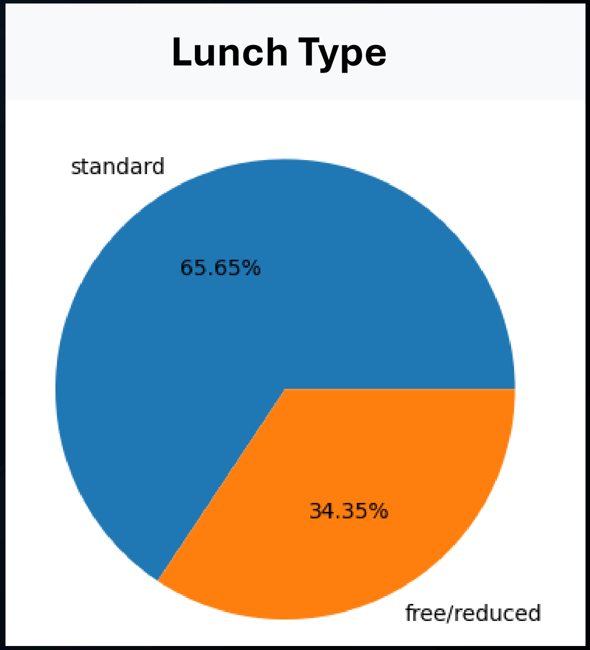
Categorical Values Exploration

```
#pandas.value_counts()--> devuelve usa sere con valores unic

#Nombres actualizados:
#"gender" : "Género",
# "race/ethnicity": "Etnia",
#"parental level of education": "Educación de los padres",
#"lunch": "Almuerzo",
#"employed": "Empleado/a",
#"test preparation course": "Curso preparatorio",

#torta: 'Género'
labels = df['Género'].value_counts().index
sizes = df['Género'].value_counts()
plt.pie(sizes,labels=labels, autopct='%1.2f%%')
plt.title('Género')
plt.show()

#torta: 'Etnia'
labels = df['Etnia'].value_counts().index
sizes = df['Etnia'].value_counts()
plt.pie(sizes,labels=labels, autopct='%1.2f%%')
plt.title('Etnia')
plt.show()

#torta: 'Empleado/a'
labels = df['Empleado/a'].value_counts().index
sizes = df['Empleado/a'].value_counts()
plt.pie(sizes,labels=labels, autopct='%1.2f%%')
plt.title('¿Está empleado?')
plt.show()

#torta: 'Curso preparatorio'
labels = df['Curso preparatorio'].value_counts().index
sizes = df['Curso preparatorio'].value_counts()
plt.pie(sizes,labels=labels, autopct='%1.2f%%')
plt.title('¿Tomó el curso preparatorio?')
plt.show()
```









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