



# Mini-Quest: Consultas SQL + Análisis

Adentrándonos en el mundo de las queries en SQL



# Proyecto en 2 partes

## Parte 1: SQL

### Queries en SQL

En donde trabajamos con operaciones lógicas, operaciones numéricas y con strings, agregaciones...

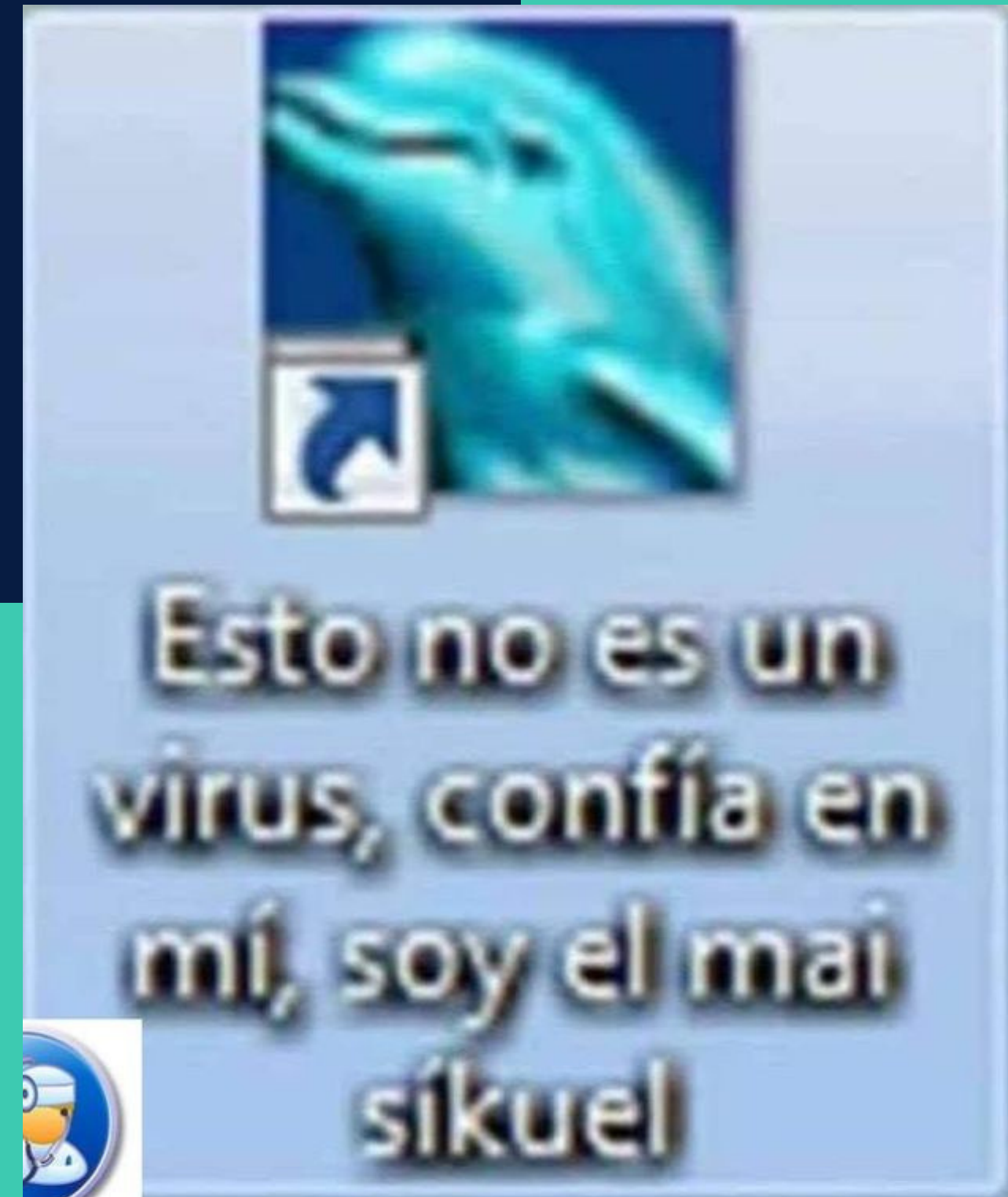
También entramos con trabajos de agrupación: joins, group bys, order bys...

## Parte 2: EDA

### EDA en Python

Ploteamos algunas interpretaciones de los CSV importados a través de las queries por SQL

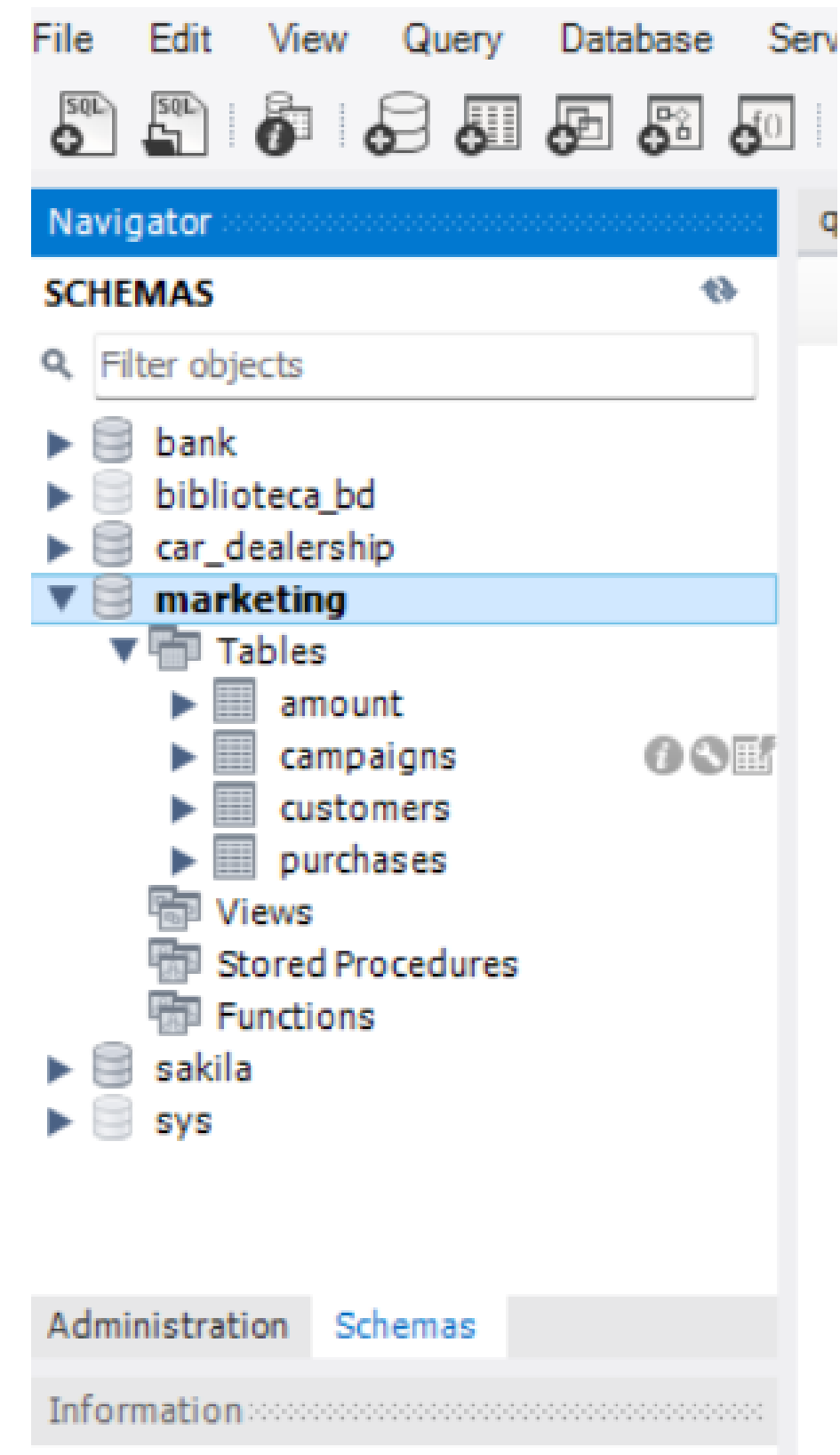
# QUERIES





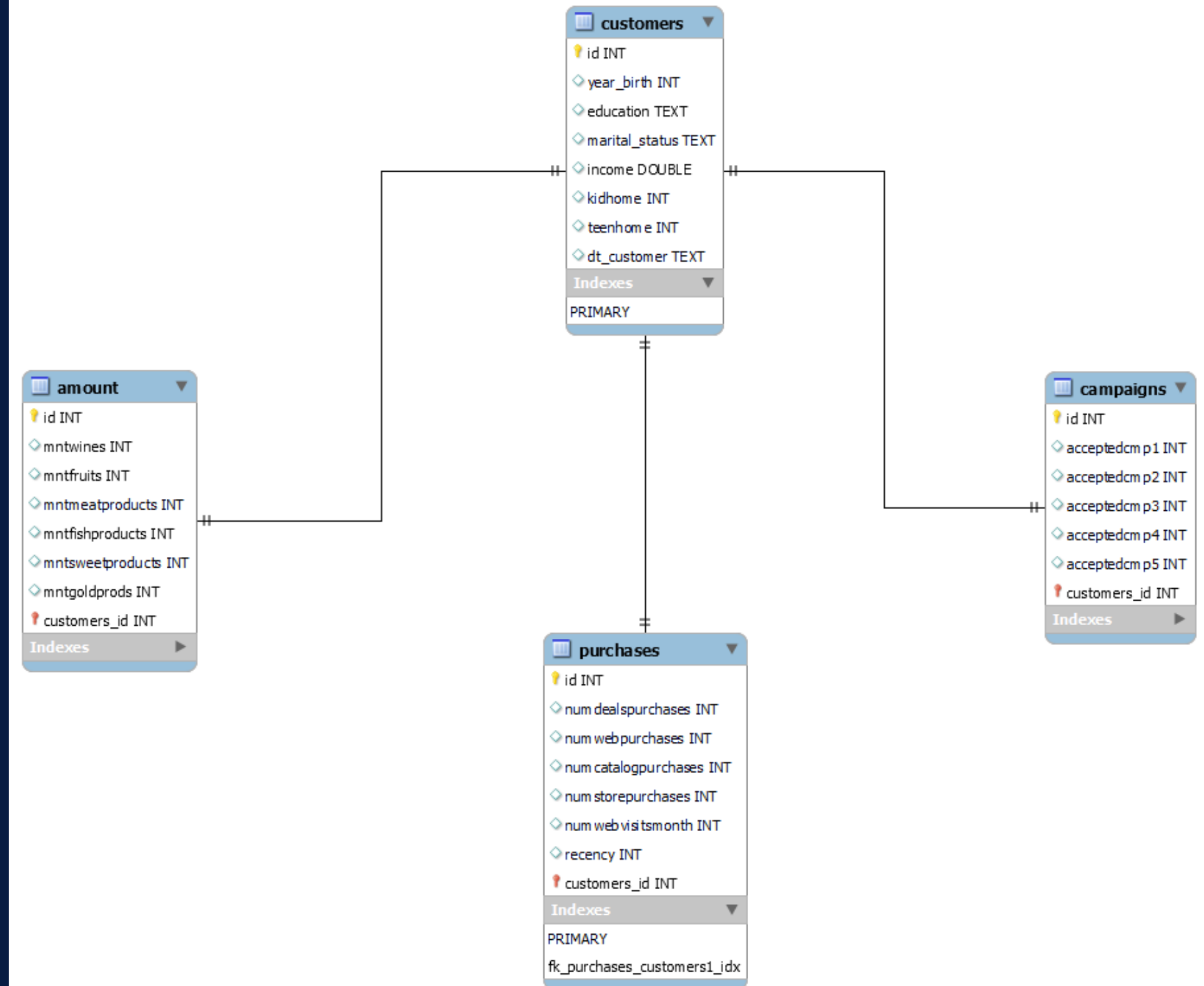
# Importamos DB y tablas

A través de Table **Data Import Wizard**



# Trazamos diagrama EER

Con **Reverse Engineer** visualizamos todo el esquema con el que trabajaremos



# Trabajamos con tablas individualmente

```
36 #####
37 ### CUSTOMERS #####
38 #####
39
40 -- AVERAGE INCOME PER EDUCATION LEVEL
41 • SELECT education,
42     COUNT(id) AS n_of_clients,
43     ROUND(AVG(2024 - year_birth),0) AS average_age,
44     ROUND(AVG(income),1) AS average_income,
45     ROUND(AVG(kidhome),2) AS average_kids_at_home,
46     ROUND(AVG(teenhome),2) AS average_teens_at_home
47 FROM customers
48 GROUP BY education
49 ORDER BY n_of_clients DESC;
50
51 -- AVERAGE INCOME PER MARITAL STATUS
52 • SELECT marital_status,
53     COUNT(id) AS n_of_clients,
54     ROUND(AVG(2024 - year_birth),0) AS average_age,
55     ROUND(AVG(income),1) AS average_income,
56     ROUND(AVG(kidhome),2) AS average_kids_at_home,
57     ROUND(AVG(teenhome),2) AS teens_at_home
```

# Y con varias tablas unidas a través de Join

```
139 -- AMOUNT SPENT AND PURCHASES PER MARITAL STATUS
140 • SELECT cus.marital_status,
141        COUNT(cus.id) AS n_of_clients,
142        SUM(amo.mntwines) AS total_wine,
143        SUM(amo.mntfruits) AS total_fruit,
144        SUM(amo.mntmeatproducts) AS total_meat,
145        SUM(amo.mntfishproducts) AS total_fish,
146        SUM(amo.mntsweetproducts) AS total_sweet,
147        SUM(amo.mntgoldprods) AS total_gold,
148        SUM(amo.mntwines + amo.mntfruits + amo.mntmeatproducts + amo.mntfishproducts + amo.mntsweetproducts + amo.mntgoldprods) AS total_all_products,
149        SUM(pur.numwebpurchases) AS web_purchases,
150        SUM(pur.numcatalogpurchases) AS catalog_purchases,
151        SUM(pur.numstorepurchases) AS store_purchases,
152        SUM(pur.numwebpurchases + pur.numcatalogpurchases + pur.numstorepurchases) AS total_purchases
153 FROM customers AS cus
154 JOIN amount AS amo
155 ON cus.id = amo.id
156 JOIN purchases AS pur
157 ON amo.id = pur.id
158 WHERE marital_status <> "Absurd" AND marital_status <> "YOLO"
159 GROUP BY cus.marital_status
160 ORDER BY n_of_clients DESC;
```

# EDA

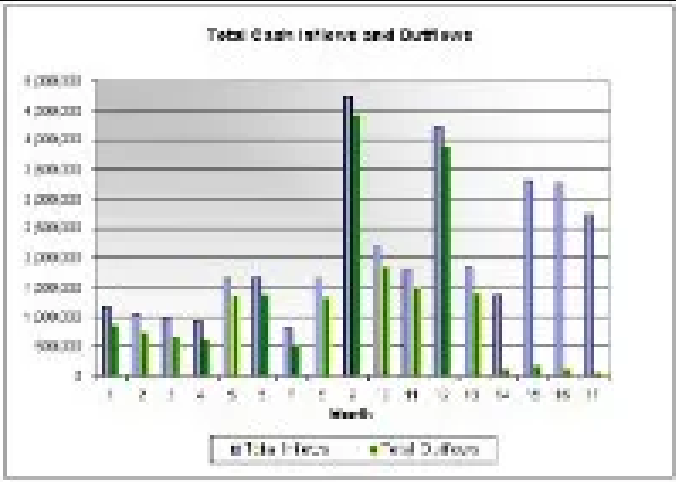


WHEN DATA IS IN TABLE FORM

ID	NAME	CLASS	MARK	SEX
1	John Doe	Four	75	female
2	Mike Ruiz	Three	85	male
3	Amel	Three	65	male
4	Krish Star	Four	80	female
5	John Mike	Four	90	female
6	Alex John	Four	65	male
7	My John Bob	Fifth	78	male
8	Amel	Five	85	male
9	Tes Coy	Six	70	male
10	Dig John	Four	55	female



WHEN DATA IS IN PLOT





# Ploteamos en Python

De los datasets exportados por las queries en SQL

## Data Extraction

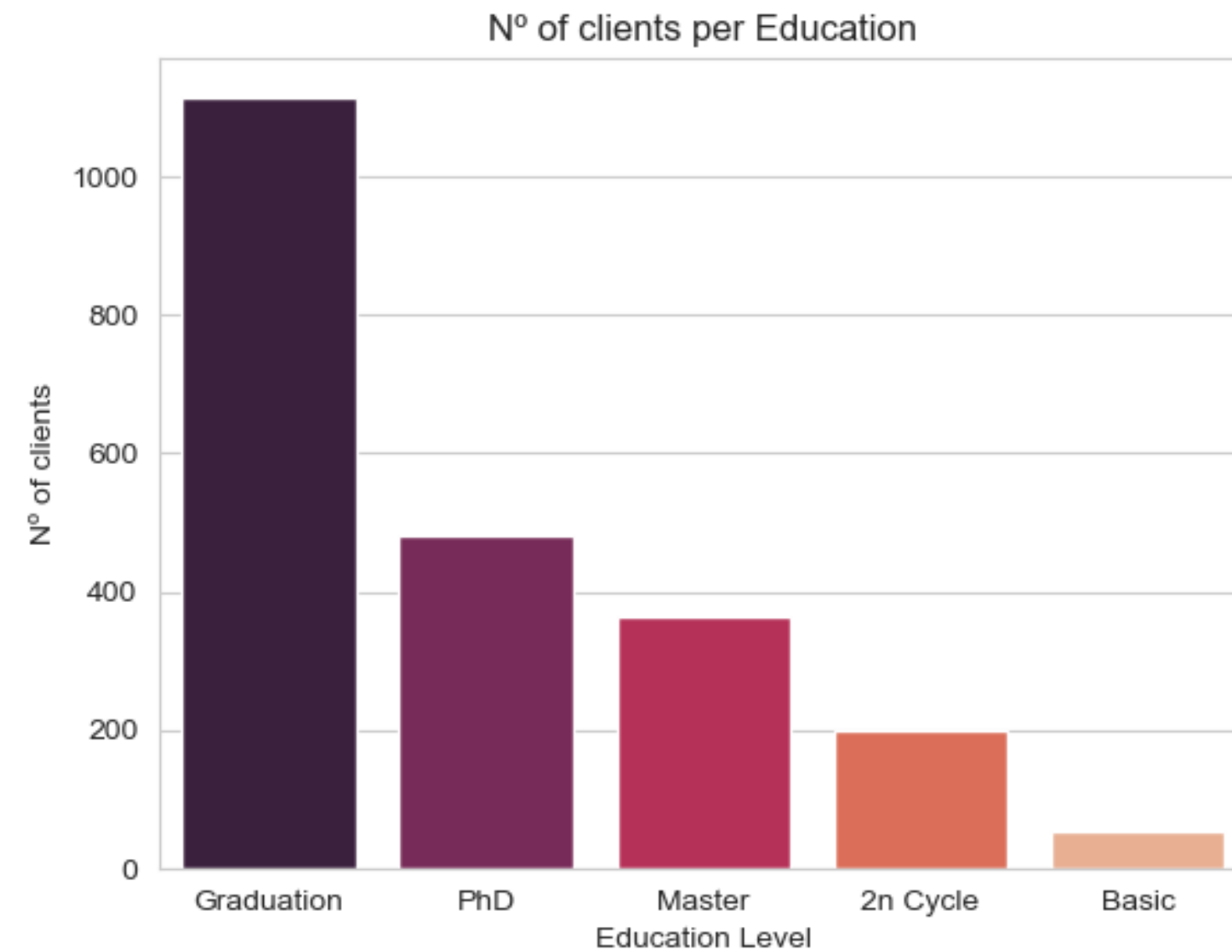
```
In [2]: income_edu = pd.read_csv("average_income_per_education.csv")
In [3]: income_mari = pd.read_csv("average_income_per_marital_status.csv")
In [4]: cmp = pd.read_csv("campaigns_statistics.csv")
In [5]: deal = pd.read_csv("deal_statistics.csv")
In [6]: pur = pd.read_csv("purchases_statistics.csv")
In [7]: sp_pur_edu = pd.read_csv("spent_amount_and_purchases_per_education.csv")
In [8]: sp_pur_mari = pd.read_csv("spent_amount_and_purchases_per_marital_status.csv")
In [9]: sp = pd.read_csv("spent_amount_statistics.csv")
In [10]: cust = pd.read_csv("type_of_customers.csv")
```

# Estadísticas por educación

	education	n_of_clients	average_age	average_income	average_kids_at_home	average_teens_at_home
0	Graduation	1116	54	52720.4	0.44	0.49
1	PhD	481	58	56145.3	0.40	0.60
2	Master	365	57	52917.5	0.46	0.53
3	2n Cycle	200	52	47633.2	0.48	0.41
4	Basic	54	47	20306.3	0.63	0.09

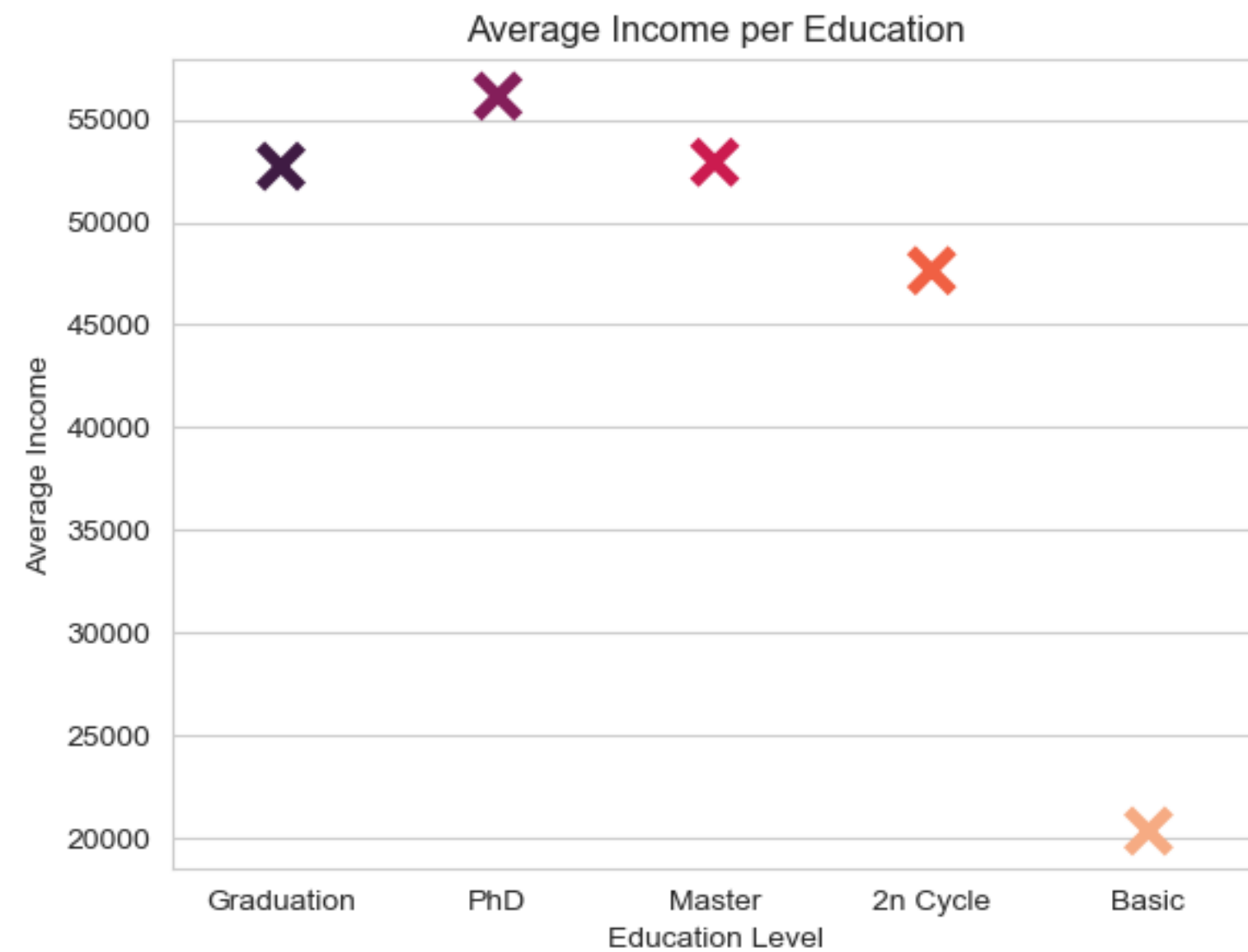
# Estadísticas por educación

Número de clientes por Educación



# Estadísticas por educación

Media de ingresos por Educación



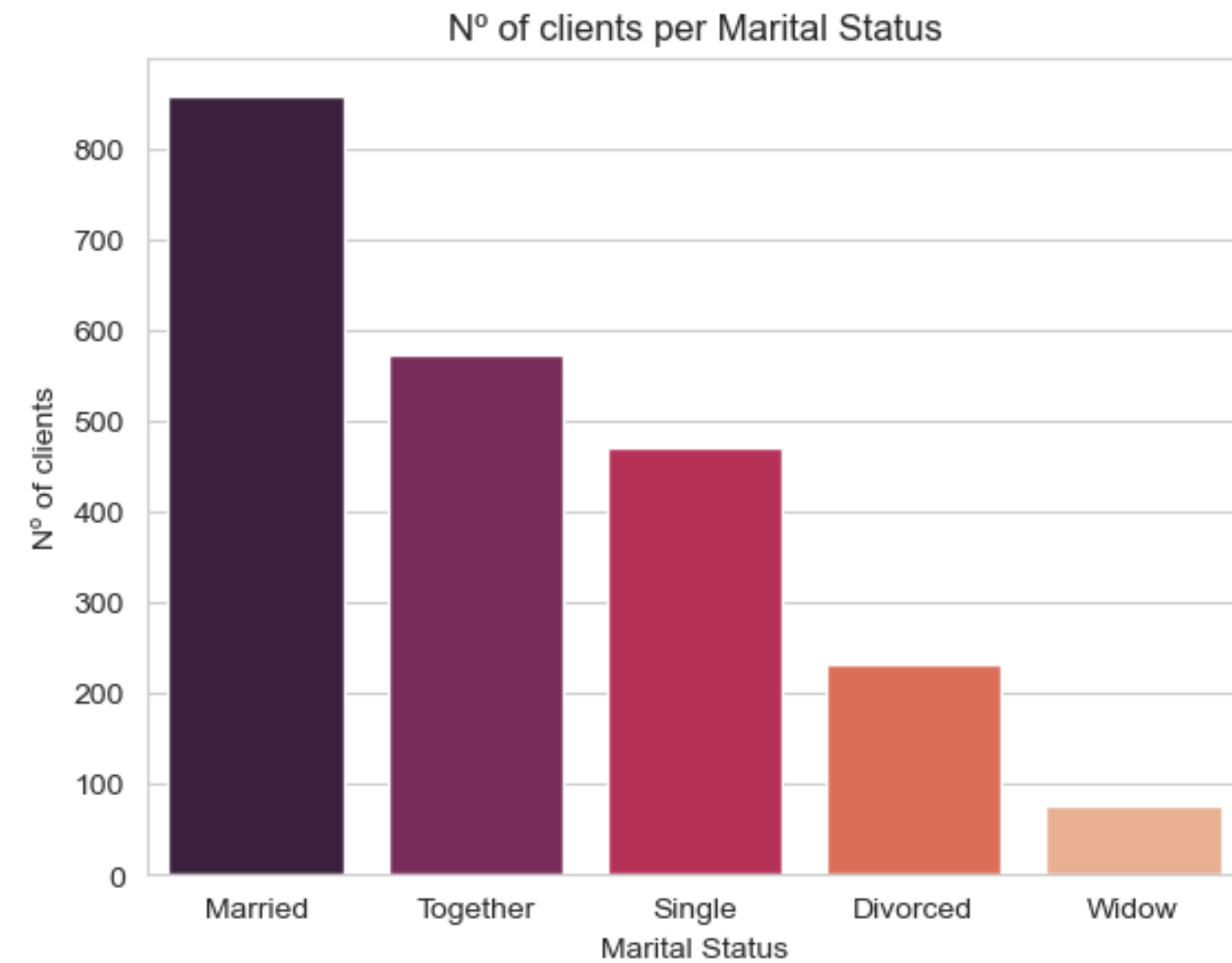


# Estadísticas por estado civil

	marital_status	n_of_clients	average_age	average_income	average_kids_at_home	teens_at_home
0	Married	857	54	51725.0	0.45	0.51
1	Together	573	56	53245.5	0.45	0.53
2	Single	471	52	50995.4	0.46	0.40
3	Divorced	232	58	52834.2	0.41	0.59
4	Widow	76	65	56481.6	0.24	0.64

# Estadísticas por estado civil

Número de clientes por Estado Civil



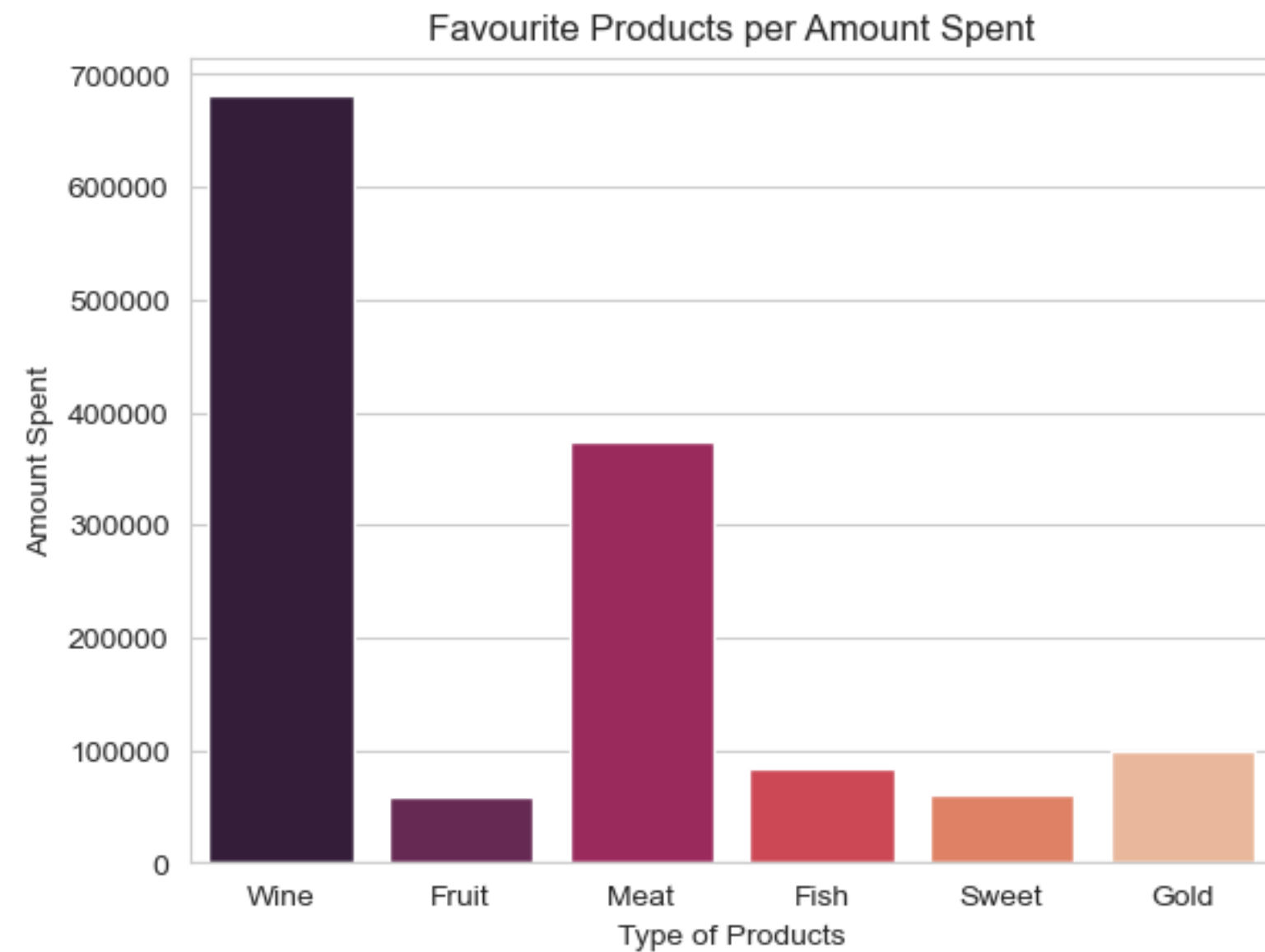
# Estadísticas por estado civil

Media de ingresos por Estado Civil



# Estadísticas por Gasto

	total_wine	total_fruit	total_meat	total_fish	total_sweet	total_gold	total_all_products
0	680816	58917	373968	84057	60621	98609	1356988

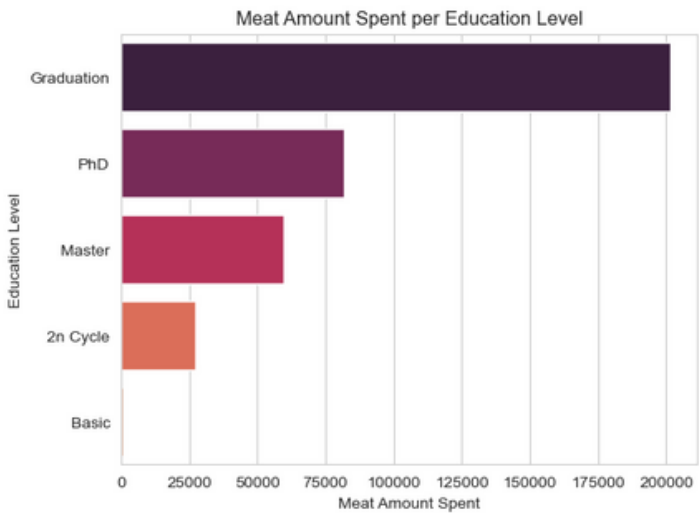
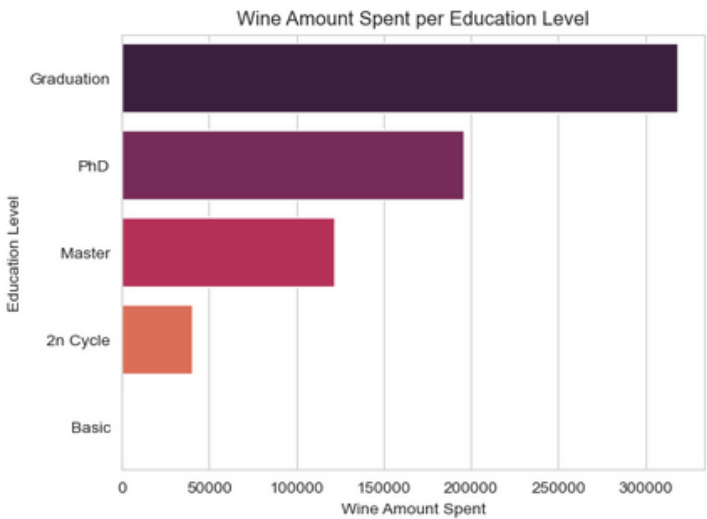




# Estadísticas por Gasto

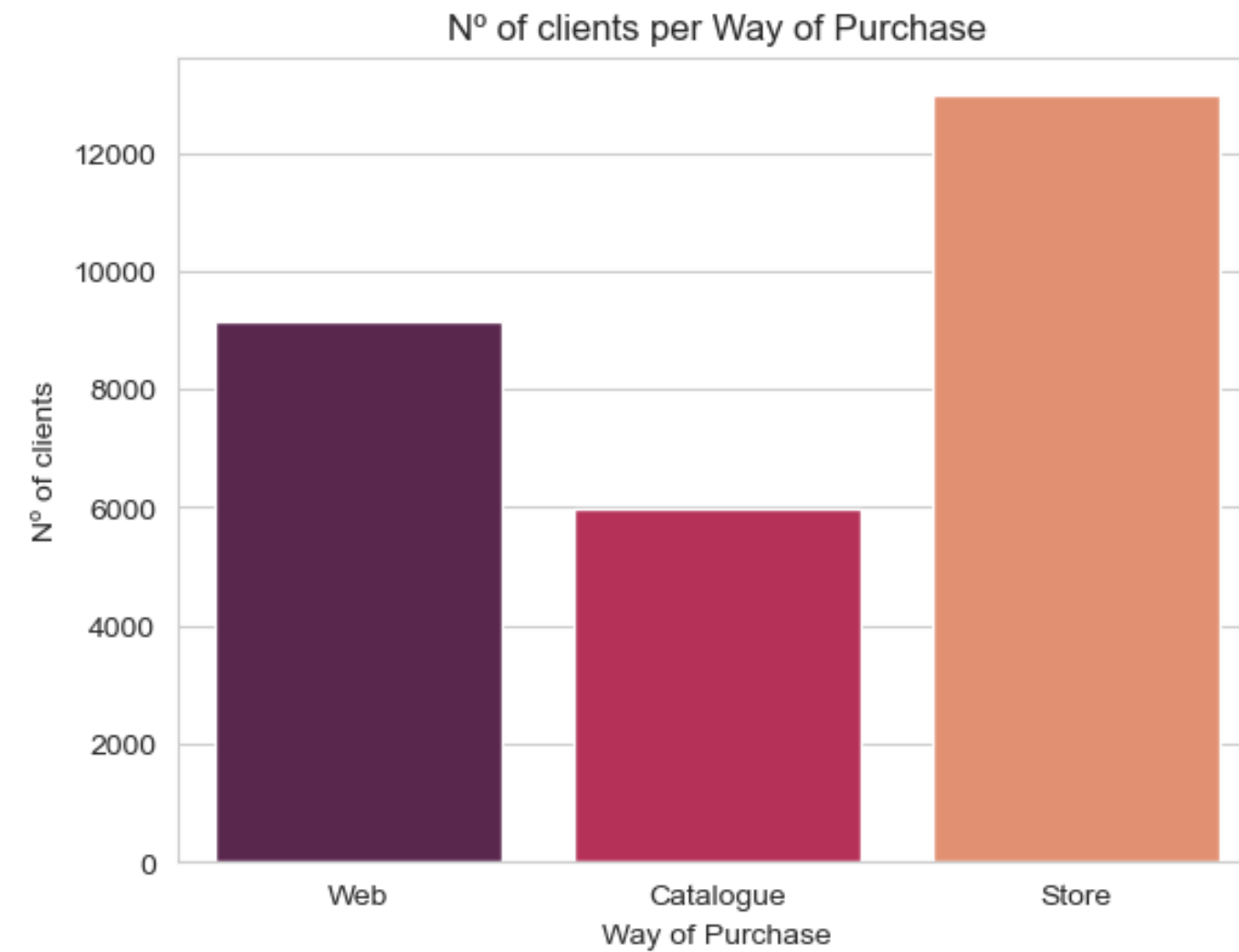
Gasto por Educación

	education	total_wine	total_fruit	total_meat	total_fish	total_sweet
0	Graduation	318111	34441	201319	48453	34915
1	PhD	195874	9690	81644	12928	9787
2	Master	121538	7802	59466	11495	7595
3	2n Cycle	40169	5872	27016	9608	6945
4	Basic	391	600	618	921	654



# Estadísticas por Modo Compra

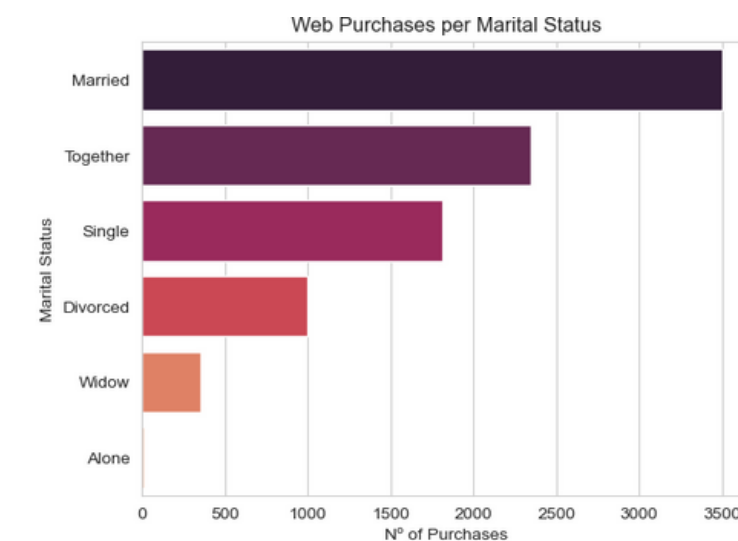
	web_purchases	catalog_purchases	store_purchases	total_purchases
0	9150	5963	12970	28083



# Estadísticas por Modo de compra

Compra por Estado Civil

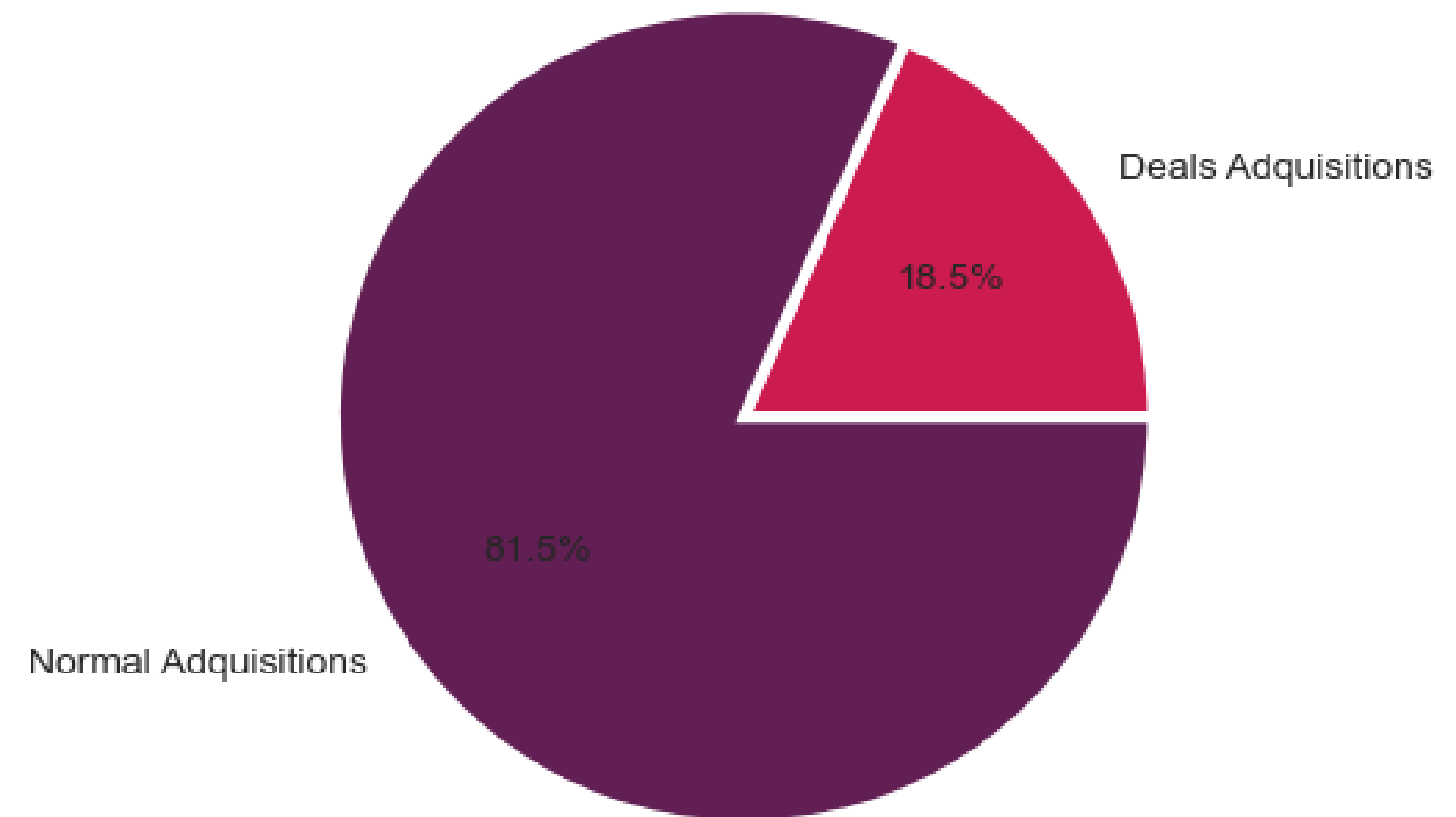
	marital_status	web_purchases	catalog_purchases	store_purchases
0	Married	3501	2254	5013
1	Together	2351	1535	3298
2	Single	1814	1240	2674
3	Divorced	1000	620	1350
4	Widow	351	251	483
5	Alone	15	2	12



# Estadísticas de Oferta de Compra

	n_of_deals	total_purchases	deals_vs_purchases
0	5208	28083	18.55

Deals vs Normal Acquisitions





# Estadísticas de Aceptación de Campaña

	total_cmp1	total_cmp2	total_cmp3	total_cmp4	total_cmp5
0	144	30	163	167	163

