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v Ústí nad Labem

Přírodovědecká fakulta, Katedra informatiky

OLAP a ClickHouse

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1 Volba OLAP

Pro zápočtovou práci jsem si zvolila open-source nástroj **ClickHouse**. V tomto projektu pracuji s ClickHouse pomocí Docker containeru, existuje však i cloudová služba ClikHouse Cloud.

2 Datová sada

Datovou sadu, se kterou pracuji, lze stáhnout z Kaggle [1]. Jedná se o uměle vytvořená data simulující prodeje v maloobchodu. V datová sadě jsem si upravili formáty hodnot některých sloupců (např.: Customer ID – CUST001 -> 1). Dále jsem ošetřila, aby se v datech nevyskytovaly duplicitní záznamy či chybějící hodnoty.

1. **Transaction ID:** A unique identifier for each transaction, allowing tracking and reference.
2. **Date:** The date when the transaction occurred, providing insights into sales trends over time.
3. **Customer ID:** A unique identifier for each customer, enabling customer-centric analysis.
4. **Gender:** The gender of the customer (Male/Female), offering insights into gender-based purchasing patterns.
5. **Age:** The age of the customer, facilitating segmentation and exploration of age-related influences.
6. **Product Category:** The category of the purchased product (e.g., Electronics, Clothing, Beauty), helping understand product preferences.
7. **Quantity:** The number of units of the product purchased, contributing to insights on purchase volumes.
8. **Price per Unit:** The price of one unit of the product, aiding in calculations related to total spending.
9. **Total Amount:** The total monetary value of the transaction, showcasing the financial impact of each purchase.

Obrázek 1: Informace ke sloupcům datasetu

2.1 Rozdělení do zón

Vrstvy datového skladu:

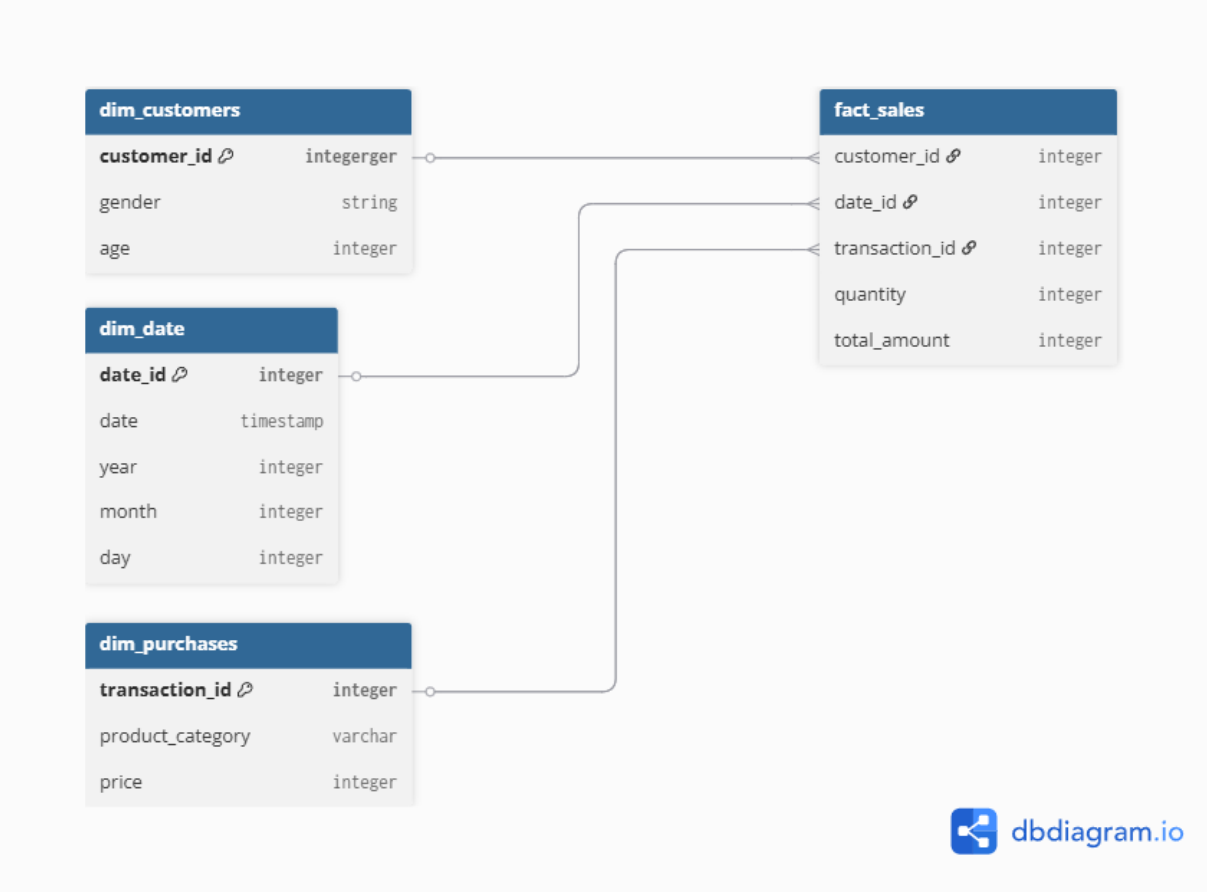
- **Raw Zone** – surová data v původní podobě, tj. stažený dataset `sales_data.csv` z Kaggle
- **Cleansed Zone** – pročištěná a rozdělená datadata, soubory pro import do databáze (`customers_dim.csv`, `date_dim.csv`, `purchases_dim.csv`, `fact.csv`)
- **Transformed Zone** – hvězdicová struktura (tabulka faktů + dimenze) a následné řezy datovou kostkou (analytické dotazy)

[1] https://www.kaggle.com/datasets/mohammadtalib786/retail-sales-dataset

3 Datová kostka

Použila jsem schéma **Hvězda** se třemi dimenzemi a jednou faktovou tabulkou.

- **Dimenze Zákazníků (dim_customers)**
  – Customer ID (PK), Gender, Age
- **Dimenze Času (dim_date)**
  – Date ID (PK), Date, Year, Month, Day
- **Dimenze Objednávek (dim_purchases)**
  - Transaction ID (PK), Product Category, Price per Unit
- **Tabulka faktů (fact_sales)**
  – Customer ID (FK), Date ID (FK), Transaction ID (FK), Quantity, Total Amount



Obrázek 2: ERD diagram

3.1 Tvorba schématu Hvězda

3.1.1 Vytvoření tabulek

```
CREATE DATABASE IF NOT EXISTS dwh_sales;
USE dwh_sales;

CREATE TABLE dim_customers (
    customer_id UInt32,
    gender String,
    age UInt8,
    PRIMARY KEY (customer_id)
) ENGINE = MergeTree()
ORDER BY customer_id;


CREATE TABLE dim_date (
    date_id UInt32,
    date Date,
    day UInt8,
    month UInt8,
    year UInt16,
    PRIMARY KEY (date_id)
) ENGINE = MergeTree()
ORDER BY date_id;


CREATE TABLE dim_purchases (
    transaction_id UInt32,
    product_category String,
    price Float32,
    PRIMARY KEY (transaction_id)
) ENGINE = MergeTree()
ORDER BY transaction_id;


CREATE TABLE fact_sales (
    customer_id UInt32,
    date_id UInt32,
    transaction_id UInt32,
    quantity UInt32,
    total_amount Float32
) ENGINE = MergeTree()
ORDER BY (customer_id, date_id, transaction_id);
```

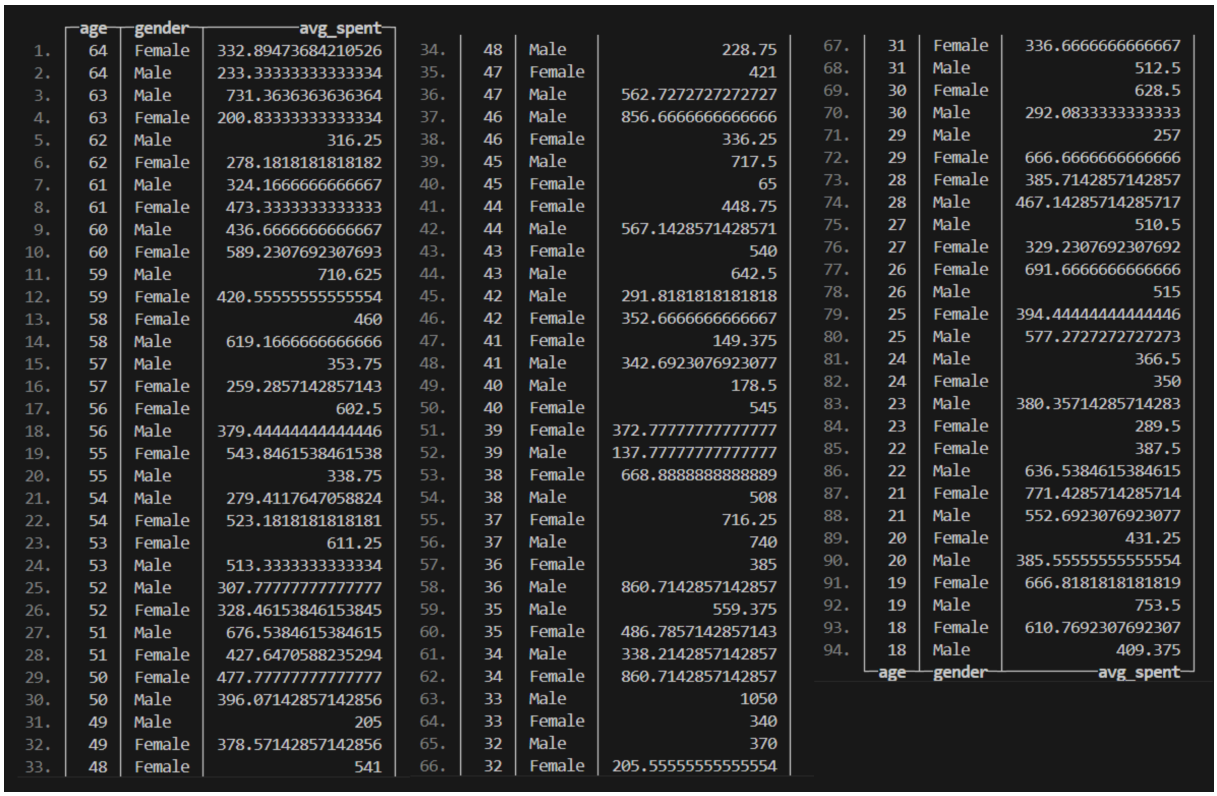
3.1.2 Import pročištěných dat

```
#!/bin/bash

CONTAINER=clickhouse-server
DB=dwh_sales

docker exec -i $CONTAINER clickhouse-client --query="INSERT␣INTO␣$DB.dim_customers␣
    FORMAT␣CSVWithNames" < ./data/customers_dim.csv

docker exec -i $CONTAINER clickhouse-client --query="INSERT␣INTO␣$DB.dim_date␣
    FORMAT␣CSVWithNames" < ./data/date_dim.csv

docker exec -i $CONTAINER clickhouse-client --query="INSERT␣INTO␣$DB.dim_purchases␣
    FORMAT␣CSVWithNames" < ./data/purchases_dim.csv

docker exec -i $CONTAINER clickhouse-client --query="INSERT␣INTO␣$DB.fact_sales␣
    FORMAT␣CSVWithNames" < ./data/fact.csv
```

4 Řezy datovou kostkou – Dotazy nad daty

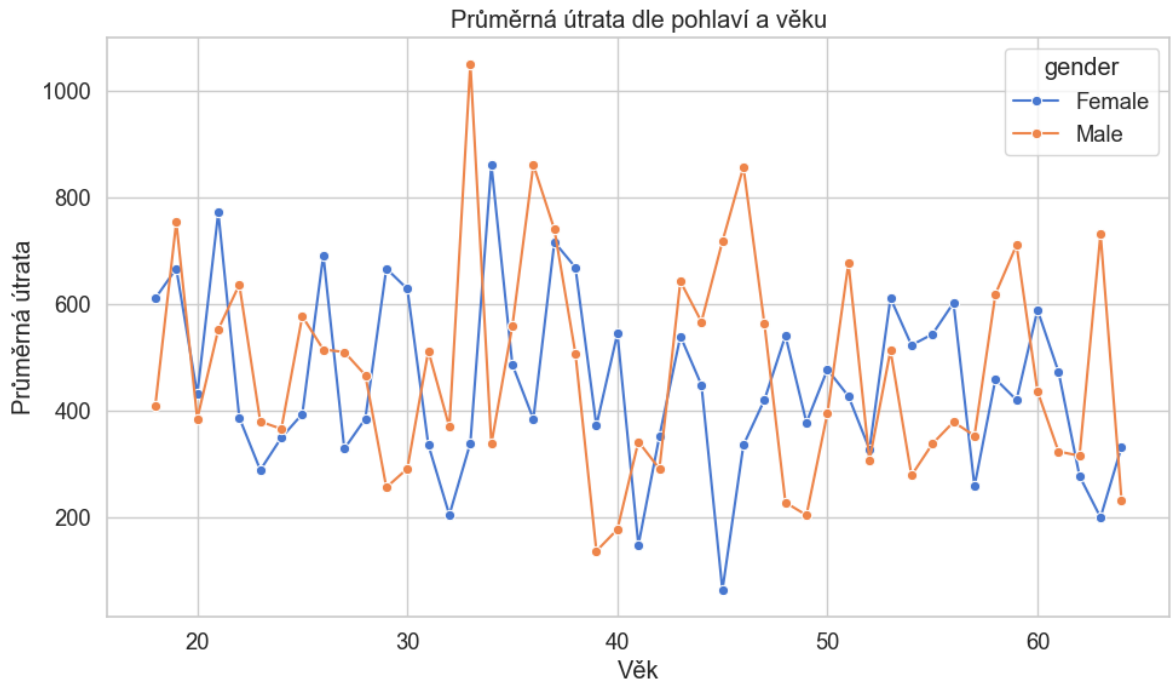
4.1 Průměrná útrata dle pohlaví a věku

```
SELECT c.age, c.gender, AVG(f.total_amount) AS avg_spent
FROM fact_sales f
JOIN dim_customers c ON f.customer_id = c.customer_id
GROUP BY c.age, c.gender
ORDER BY age DESC;
```



	age	gender	avg_spent
1.	64	Female	332.89473684210526
2.	64	Male	233.33333333333334
3.	63	Male	731.3636363636364
4.	63	Female	200.83333333333334
5.	62	Male	316.25
6.	62	Female	278.1818181818182
7.	61	Male	324.1666666666667
8.	61	Female	473.3333333333333
9.	60	Male	436.6666666666667
10.	60	Female	589.2307692307693
11.	59	Male	710.625
12.	59	Female	420.55555555555554
13.	58	Female	460
14.	58	Male	619.1666666666666
15.	57	Male	353.75
16.	57	Female	259.2857142857143
17.	56	Female	602.5
18.	56	Male	379.44444444444446
19.	55	Female	543.8461538461538
20.	55	Male	338.75
21.	54	Male	279.4117647058824
22.	54	Female	523.1818181818181
23.	53	Female	611.25
24.	53	Male	513.3333333333334
25.	52	Male	307.77777777777777
26.	52	Female	328.46153846153845
27.	51	Male	676.5384615384615
28.	51	Female	427.6470588235294
29.	50	Female	477.77777777777777
30.	50	Male	396.07142857142856
31.	49	Male	205
32.	49	Female	378.57142857142856
33.	48	Female	541
34.	48	Male	228.75
35.	47	Female	421
36.	47	Male	562.7272727272727
37.	46	Male	856.6666666666666
38.	46	Female	336.25
39.	45	Male	717.5
40.	45	Female	65
41.	44	Female	448.75
42.	44	Male	567.1428571428571
43.	43	Female	540
44.	43	Male	642.5
45.	42	Male	291.8181818181818
46.	42	Female	352.6666666666667
47.	41	Female	149.375
48.	41	Male	342.6923076923077
49.	40	Male	178.5
50.	40	Female	545
51.	39	Female	372.77777777777777
52.	39	Male	137.77777777777777
53.	38	Female	668.8888888888889
54.	38	Male	508
55.	37	Female	716.25
56.	37	Male	740
57.	36	Female	385
58.	36	Male	860.7142857142857
59.	35	Male	559.375
60.	35	Female	486.7857142857143
61.	34	Male	338.2142857142857
62.	34	Female	860.7142857142857
63.	33	Male	1050
64.	33	Female	340
65.	32	Male	370
66.	32	Female	205.55555555555554
67.	31	Female	336.6666666666667
68.	31	Male	512.5
69.	30	Female	628.5
70.	30	Male	292.0833333333333
71.	29	Male	257
72.	29	Female	666.6666666666666
73.	28	Female	385.7142857142857
74.	28	Male	467.14285714285717
75.	27	Male	510.5
76.	27	Female	329.2307692307692
77.	26	Female	691.6666666666666
78.	26	Male	515
79.	25	Female	394.44444444444446
80.	25	Male	577.2727272727273
81.	24	Male	366.5
82.	24	Female	350
83.	23	Male	380.35714285714283
84.	23	Female	289.5
85.	22	Female	387.5
86.	22	Male	636.5384615384615
87.	21	Female	771.4285714285714
88.	21	Male	552.6923076923077
89.	20	Female	431.25
90.	20	Male	385.55555555555554
91.	19	Female	666.8181818181819
92.	19	Male	753.5
93.	18	Female	610.7692307692307
94.	18	Male	409.375

age gender avg_spent

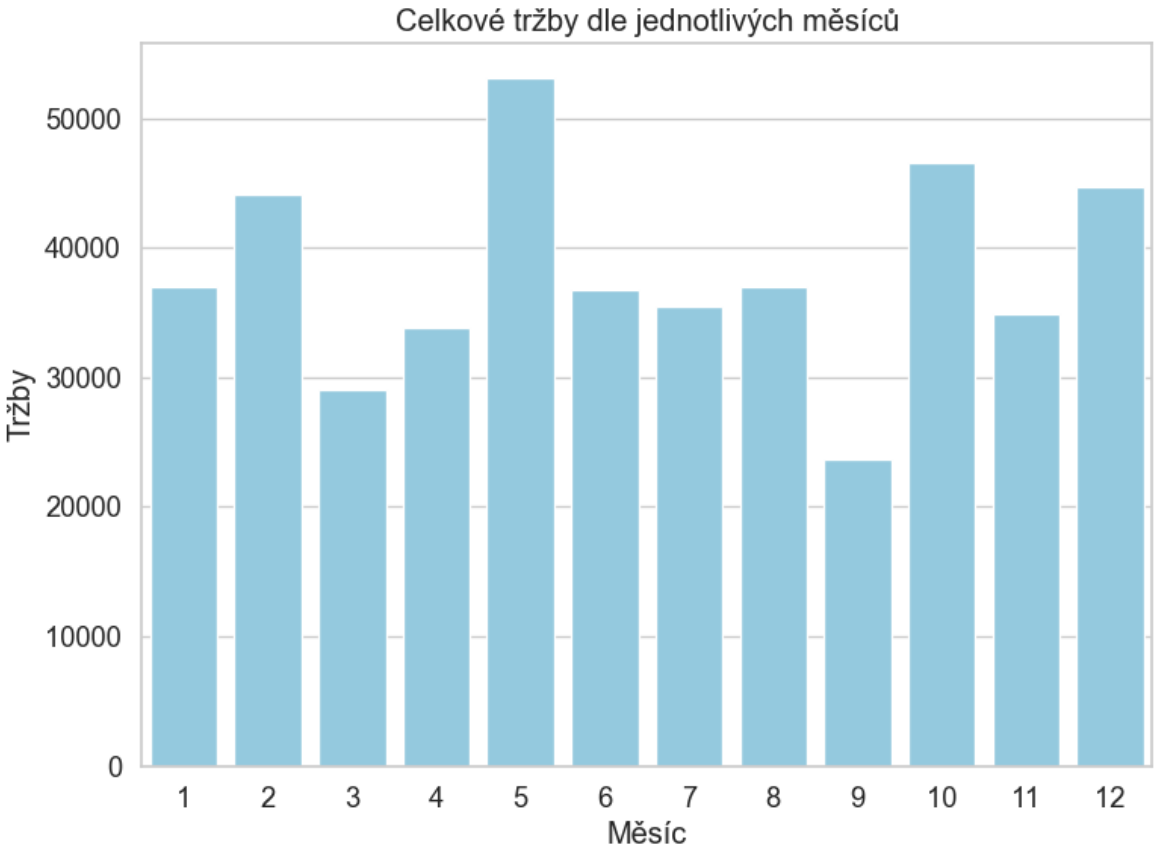


Obrázek 3: Vizualizace 1

4.2 Celkové tržby dle jednotlivých měsíců

```
SELECT d.month, SUM(f.total_amount) AS revenue
FROM fact_sales f
JOIN dim_date d ON f.date_id = d.date_id
GROUP BY d.month
ORDER BY month;
```

	month	revenue
1.	1	36980
2.	2	44060
3.	3	28990
4.	4	33870
5.	5	53150
6.	6	36715
7.	7	35465
8.	8	36960
9.	9	23620
10.	10	46580
11.	11	34920
12.	12	44690

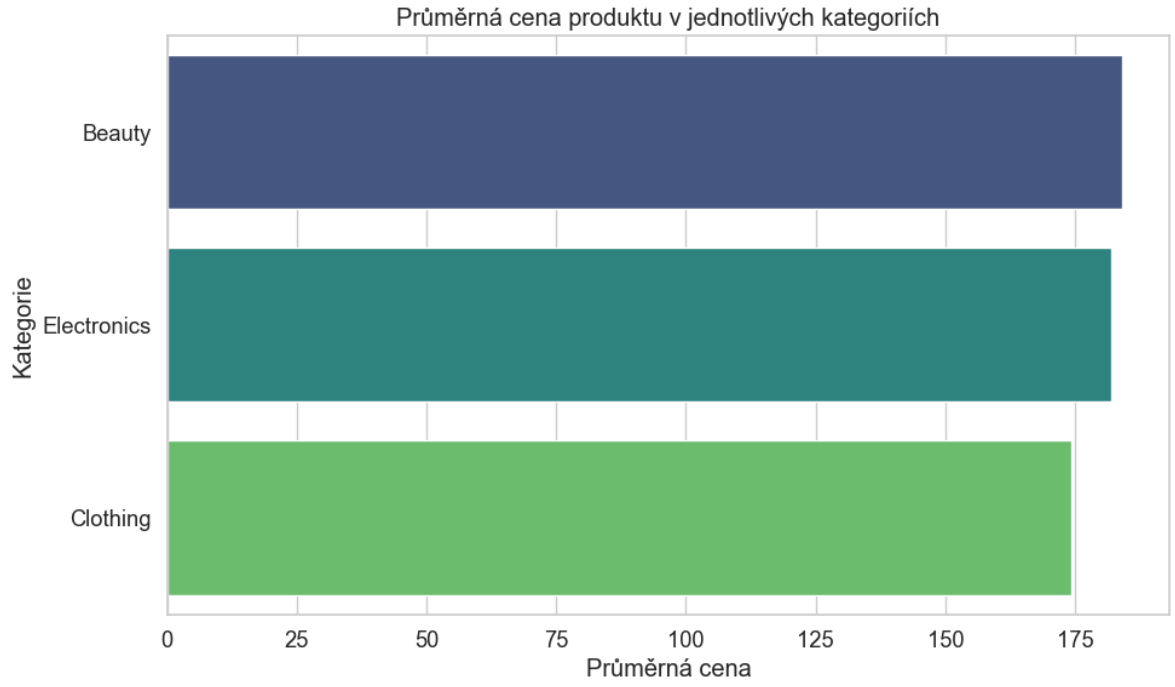


Obrázek 4: Vizualizace 2

4.3 Průměrná cena produktu v jednotlivých kategoriích

```
SELECT p.product_category, AVG(p.price) AS avg_price
FROM fact_sales f
JOIN dim_purchases p ON f.transaction_id = p.transaction_id
GROUP BY p.product_category
ORDER BY avg_price DESC;
```

	product_category	avg_price
1.	Beauty	184.05537459283389
2.	Electronics	181.90058479532163
3.	Clothing	174.28774928774928

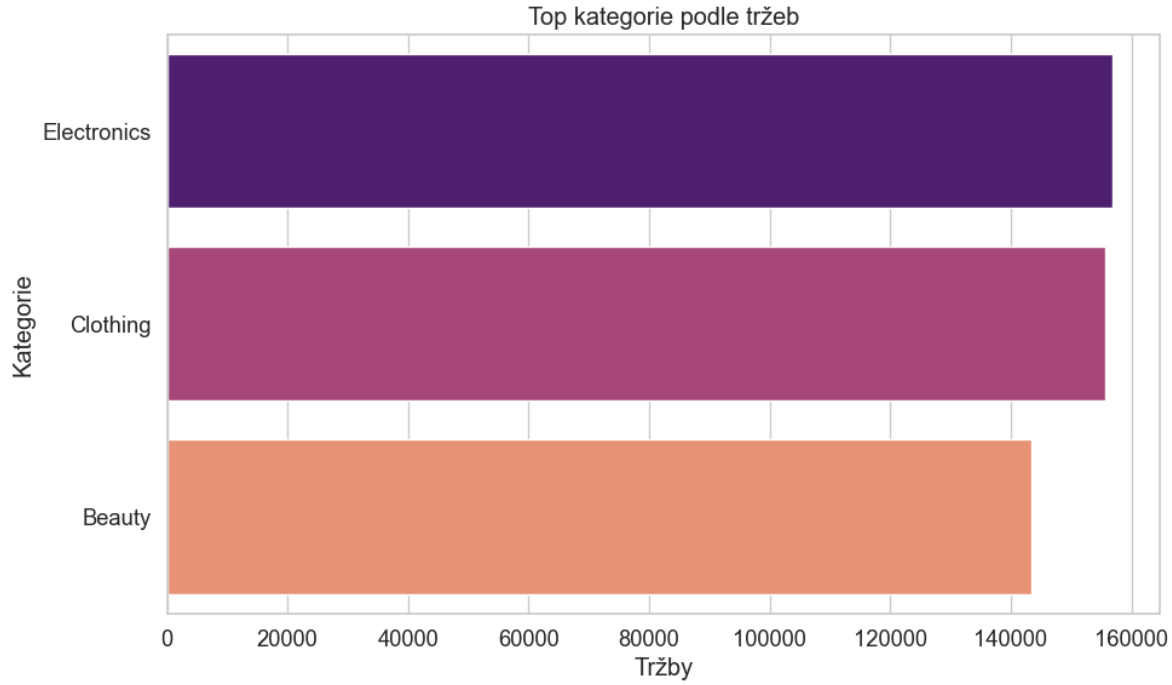


Obrázek 5: Vizualizace 3

4.4 Top kategorie podle tržeb

```
SELECT p.product_category, SUM(f.total_amount) AS revenue
FROM fact_sales f
JOIN dim_purchases p ON f.transaction_id = p.transaction_id
GROUP BY p.product_category
ORDER BY revenue DESC;
```

	product_category	revenue
1.	Electronics	156905
2.	Clothing	155580
3.	Beauty	143515

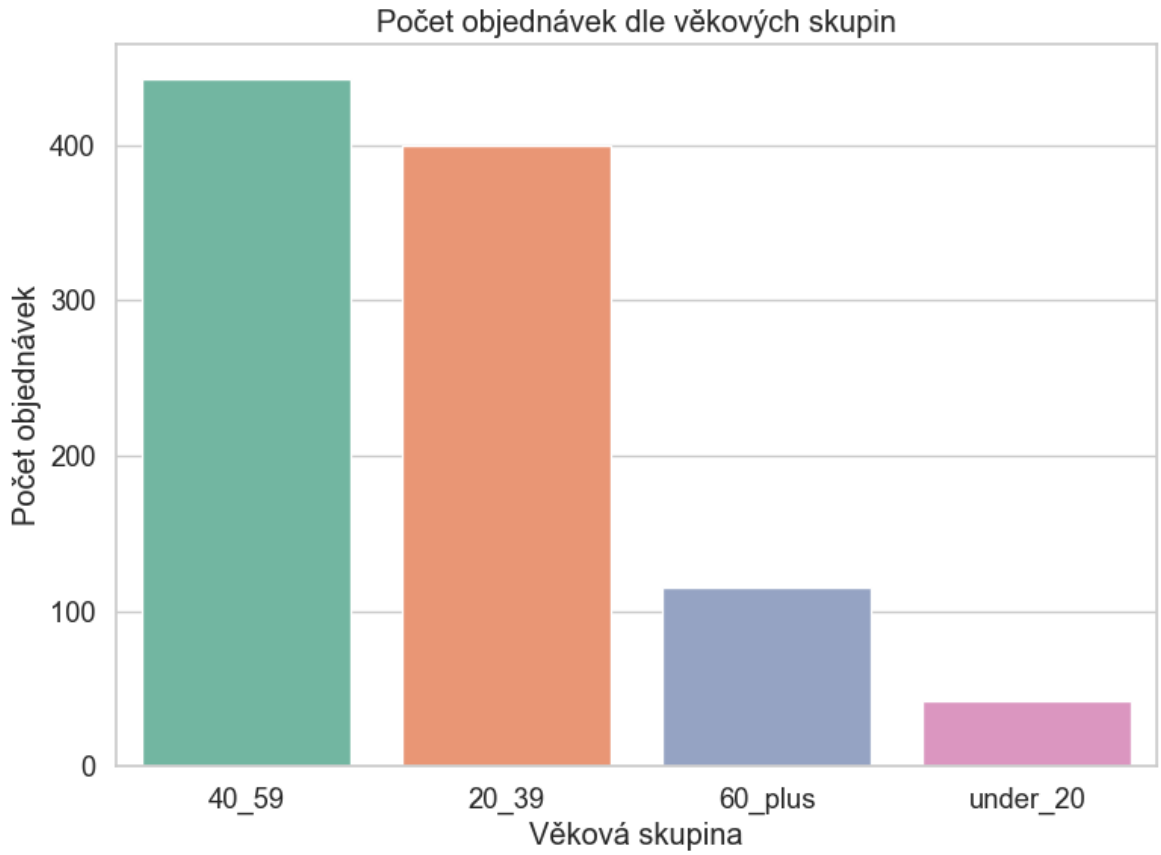


Obrázek 6: Vizualizace 4

4.5 Počet objednávek dle věkových skupin

```
SELECT
CASE
    WHEN c.age < 20 THEN 'under_20'
    WHEN c.age BETWEEN 20 AND 39 THEN '20_39'
    WHEN c.age BETWEEN 40 AND 59 THEN '40_59'
    ELSE '60_plus'
END AS age_group,
COUNT(*) AS orders
FROM fact_sales f
JOIN dim_customers c ON f.customer_id = c.customer_id
GROUP BY age_group
ORDER BY orders DESC;
```

	age_group	orders
1.	40_59	443
2.	20_39	400
3.	60_plus	115
4.	under_20	42



Obrázek 7: Vizualizace 5

5 Data Mining metoda – Shlukování (Clustering)

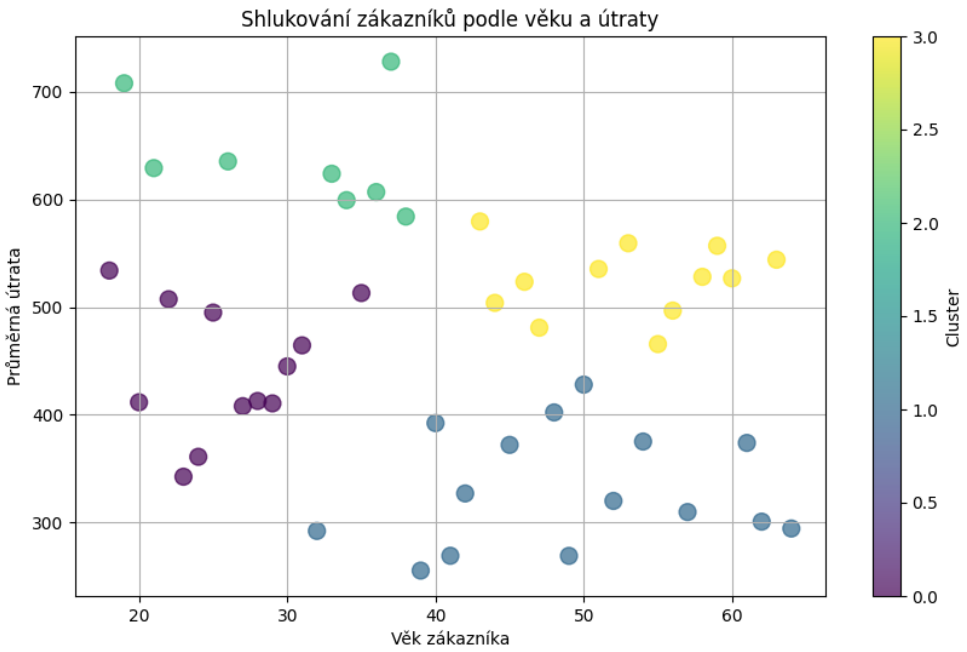
Jelikož ClickHouse nepodporuje pokročilé metody data miningu ani strojové učení, zvolila jsem postup, kdy se výstupy SQL dotazů uloží do souborů ve formátu CSV. Tyto soubory jsou následně zpracovány v jazyce Python pomocí algoritmu K-Means z knihovny scikit-learn.

Průměrná útrata zákazníků dle věku

```
SELECT c.age, AVG(f.total_amount) AS avg_spent
FROM fact_sales f
JOIN dim_customers c ON f.customer_id = c.customer_id
GROUP BY c.age
ORDER BY age
INTO OUTFILE 'sql_dm.csv' FORMAT CSV;
```

cluster	age	avg_spent
0	26.000000	442.156216
1	49.066667	332.049800
2	30.500000	639.449949
3	52.916667	525.159671

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

df = pd.read_csv("sql_dm.csv")

# Standardizace
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df)

# Shlukovani (KMeans)
kmeans = KMeans(n_clusters=4, random_state=42)
df["cluster"] = kmeans.fit_predict(X_scaled)
print(df.groupby("cluster").mean())
```



Obrázek 8: Vizualizace Shlukování

Zdroje

[1] YANDEX. *ClickHouse Documentation* [online]. 2025 [cit. 2025-06-08]. Dostupné z: `https://clickhouse.com/docs/en/`