bandcamp.com

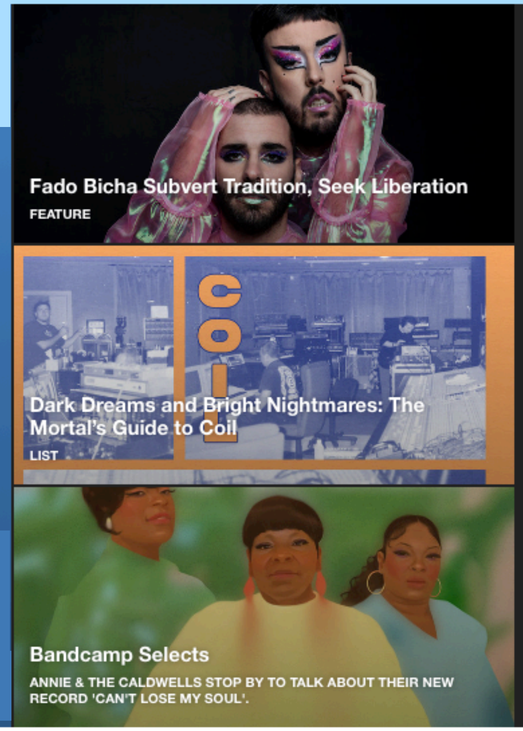
bandcamp | Search for artist, album, or track | Bandcamp Gift Cards and Merch

Browse | Vinyl | CDs | Cassettes | T-shirts | Radio | Bandcamp Daily | Best of's

Bandcamp sales

Customer behavior analysis

by Faniia Prazdnikova



Fans have paid artists **$1.47 billion** using Bandcamp, and **$194 million** in the last year.

SELLING RIGHT NOW

Limited Editioned Ca...	**Split w/ Callow**	**Fun and Games**	**Manamaê ô from Sun...**	**Block Party**	**Limited Edition 12" Bl...**	**Limited Edition 12" Bl...**	**Live in Los Angeles '24**
by Borrstahl	by Jungbluth	by Mega Mango	by Tech Support	by Sudoo	by Nowaah The Flood ...	by Nowaah The Flood ...	by King Gizzard & The ...
Sold for €15	Sold for €0.50	Sold for $10	Sold for £1	Sold for £1.50	Sold for $55.55	Sold for $55.55	Sold for $1
€3 more than the min	in Germany	$10 more than the min	in United Kingdom	in Finland	in United States	in United States	in United States

User story

CONTROL

by VIER

CONTROL 00:00 / 03:28

Digital Album

Streaming + Download

Includes unlimited streaming via the free Bandcamp app, plus high-quality download in MP3, FLAC and more.

Download available in 16-bit/44.1kHz.

Buy Digital Album €2 EUR or more

Send as Gift

1. CONTROL 03:28 info buy track

released February 14, 2025

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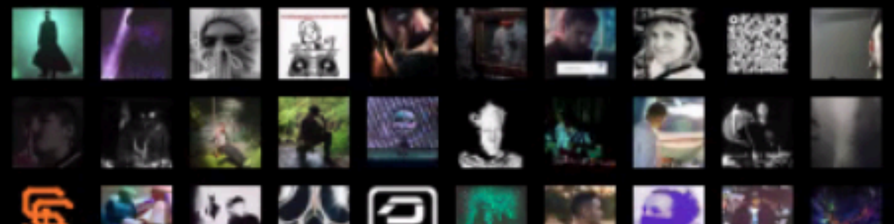
Share / Embed Wishlist

supported by



VISION
Groningen, Netherlands

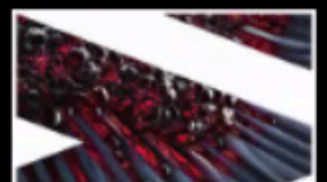
Following

Est. 2005 by NOISIA

Home to Mefjus, Machinedrum, Camo & Krooked, IMANU, The Upbeats, Tsuruda, Skeptical, Chee and many others.

visionrecordings.nl

discography



Digital Track

Enter Amount: € EUR (€2 or more)

$2.15 USD or more.

Includes unlimited streaming via the free Bandcamp app, plus high-quality download in MP3, FLAC and more.

Have a gift card? Redeem it here

Include a message to VISION.

☐ Add me to the mailing list for VISION.

Check out with PayPal | Add to cart

or use credit card

Digital Track

Enter Amount: € 3 EUR (€2 or more)

That's an extra $1.08 USD ($3.23 total)! Thanks for your generosity.

Includes unlimited streaming via the free Bandcamp app, plus high-quality download in MP3, FLAC and more.

Have a gift card? Redeem it here

Include a message to VISION.

☐ Add me to the mailing list for VISION.

Check out with PayPal | Add to cart

or use credit card

To finalize the tax and total, please provide your billing location:

Country

Germany

CONTROL
by VIER
Digital Track

€3.38 EUR

Prices include tax where applicable.

subtotal	€2.38 EUR
additional contribution	€1.00 EUR
total	€3.38 EUR

Proceed to PayPal

This is a secure, TLS-encrypted transaction.

download track
resend receipt

Subtotal:	€2.00 EUR
Additional Contribution:	€1.00 EUR
VAT:	€0.38 EUR
Total:	**€3.38 EUR**

PAYPAL *BANDCAMP

MCC 5815

-3,38 €

Pending

Digital Album

Enter Amount: $ USD (no minimum) convert

Includes high-quality download in MP3, FLAC and more. Paying supporters also get unlimited streaming via the free Bandcamp app.

Have a gift card? Redeem it here

Add me to the mailing list for Tony Longworth.

Check out with PayPal | Add to cart

or use credit card

Digital Album

Enter Amount: $ 0 USD (no minimum) convert

Have a gift card? Redeem it here

Pay $1 USD or more to add this release to your Bandcamp collection, get unlimited mobile streaming, and directly support Tony Longworth.

Alternatively, continue with zero and download to your computer.

bandcamp

Search for artist, album, or track

FREE MUSIC FOR EVERYONE

by Tony Longworth

Choose format: MP3 320 - 950.3MB *Preparing* | Need download help?

Dataset

Bandcamp sales

- Data source: Kaggle
- by Mathurin Ache
- contains 1,000,000 items
- from 9/9/2020 to 10/2/2020

_id: unique identifier combining the sale's URL and UTC timestamp.
url: the path to the item on Bandcamp. Use this column to join this dataset to the dataset of Bandcamp items.
artist_name: Name of the artist.
album_title: Title of the album, if applicable.
art_url: path to the item's art image.
item_type: denotes the type of object. a for digital albums, p for physical items, and t for digital tracks.
slug_type: also denotes the type of object. a for all albums, p for merch, and t for tracks.
utc_date: the UTC timestamp of the sale datetime.
country_code: country code of the buyer.
country: full country code name of the buyer.
item_price: price of the item in the seller's currency.
currency: the seller's currency.
amount_paid: amount paid in the seller's currency.
amount_paid_fmt: amount paid in the seller's currency, with the currency symbol.
amount_paid_usd: amount paid converted to US Dollars.
amount_over_fmt: amount voluntarily paid over the item price in the seller's currency.

Payment analysis

Setting targets

Main target: ‘amount_paid_usd’

Extra target: ‘amount_over_usd’ ???

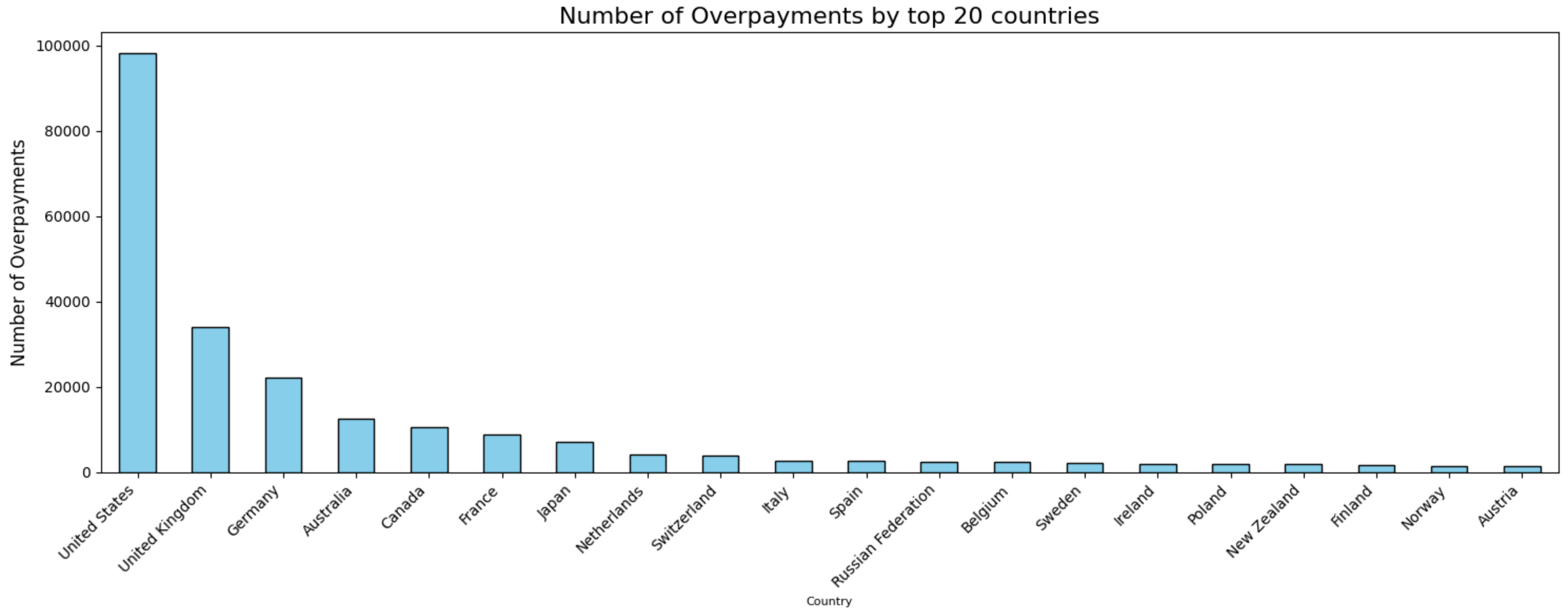
Case reference for payments

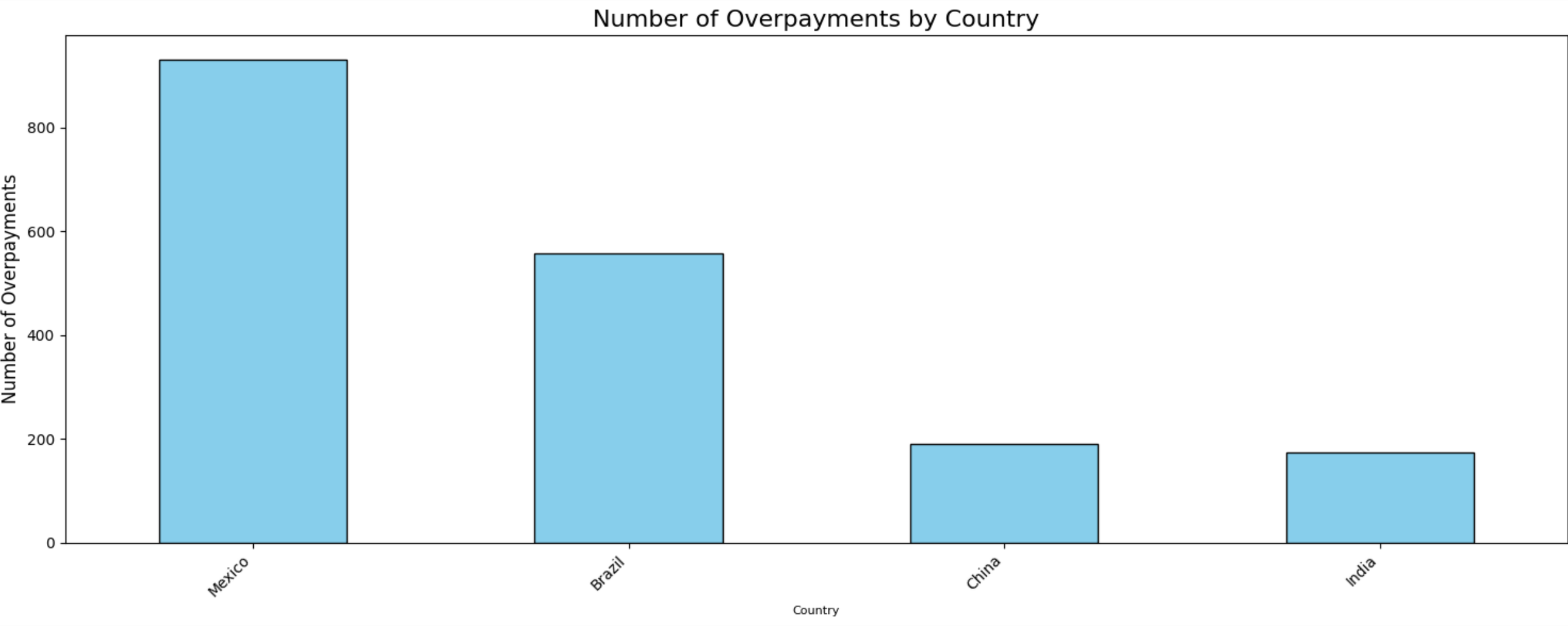
1. Overpayment: `amount_paid > item_price + amount_over_fmt`

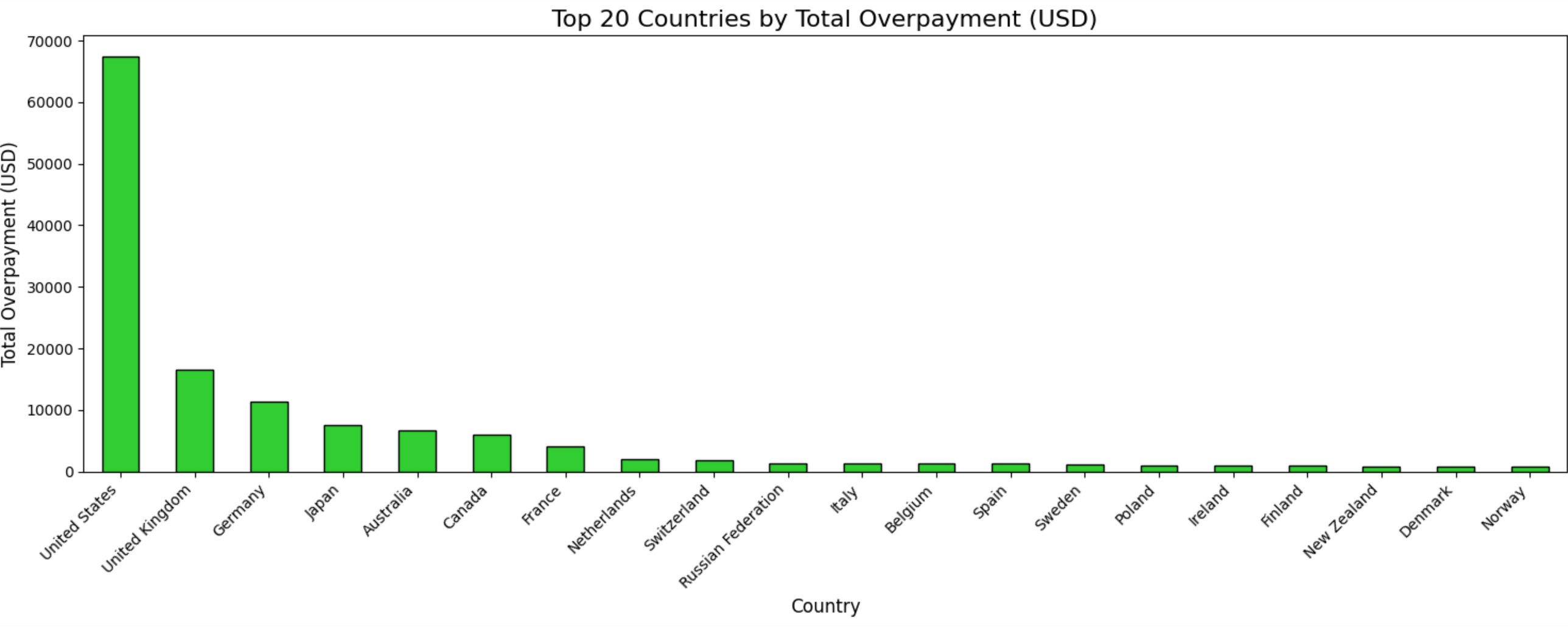
Case	Conditions	Description	Count
11	`item_price_usd > 0` and `amount_over_usd == 0`	Item was not free. No extra donation made.	86,690
12	`item_price_usd == 0` and `amount_over_usd == 0`	Item was free. No donation made.	73,709
13	`item_price_usd == 0` and `amount_over_usd > 0`	Item was free. Customer added donation.	1,035

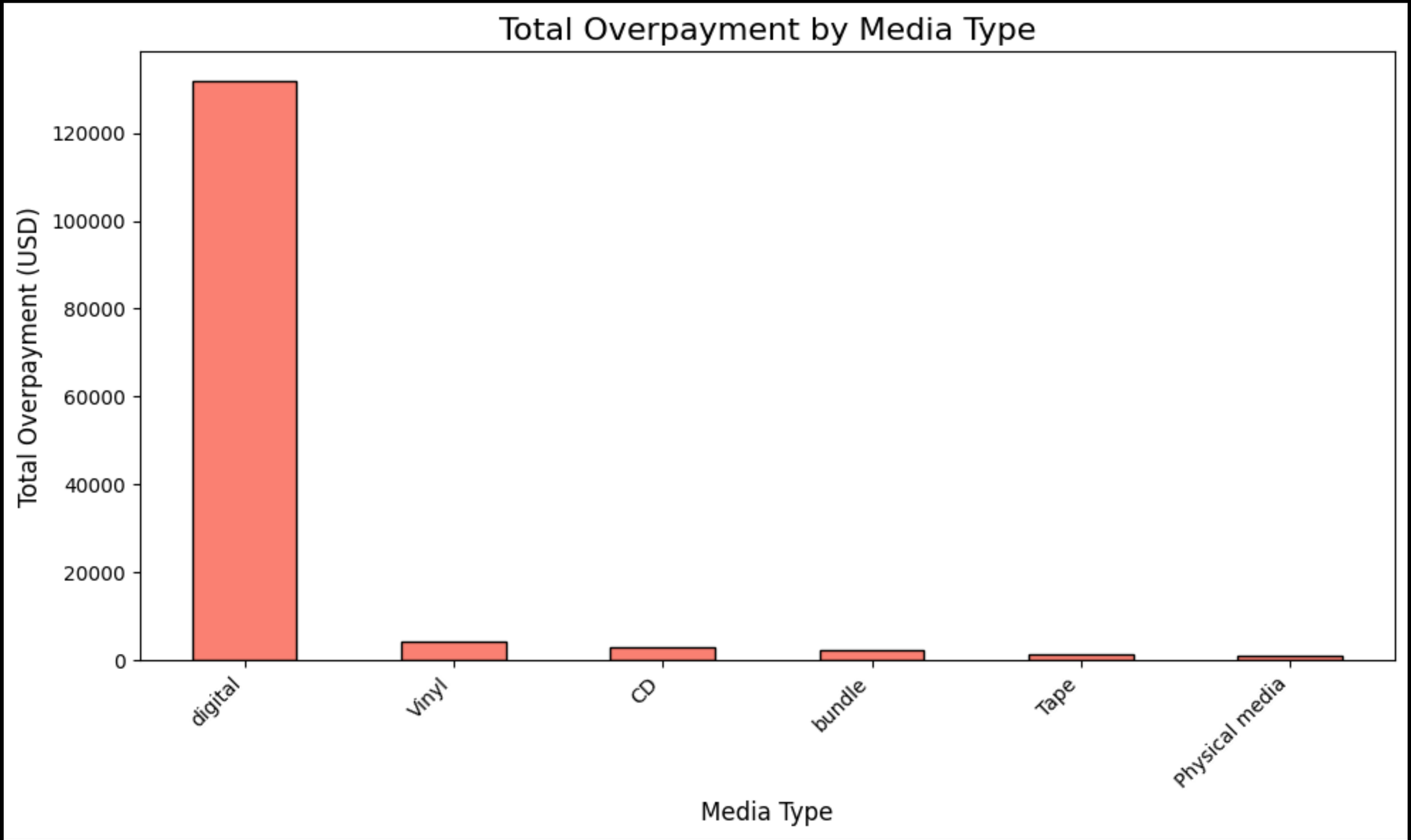
2. Underpayment: `amount_paid < item_price + amount_over_fmt`

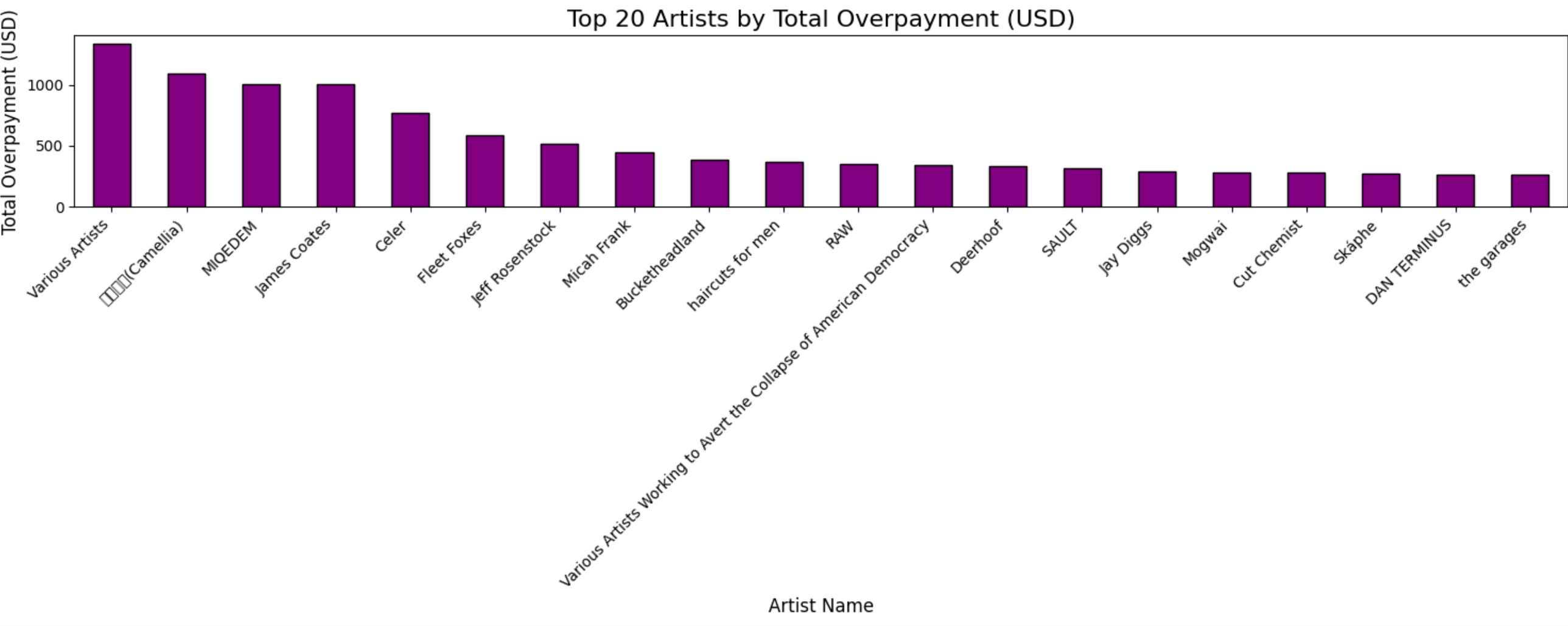
Case	Conditions	Description	Count	Notes
21	`item_price_usd == 0` and `amount_paid_usd == 0`	Item was free. Customer paid nothing — legit free access.	0	Not counted as underpayment
22	`item_price_usd > 0` and `amount_paid_usd < item_price_usd` and `amount_over_usd == 0`	Item had a price. Customer underpaid with no donation.	12,295	Discount applied?
23	`item_price_usd == 0` and `amount_over_usd > 0` and `amount_paid_usd < amount_over_usd`	Free item. Customer donated less than suggested amount.	1,683	Voluntary donation, no minimum
24	`item_price_usd > 0` and `amount_over_usd > 0` and `amount_paid_usd < item_price_usd + amount_over_usd`	Item had price + donation. Customer paid less than full total.	7,527	Discount applied?

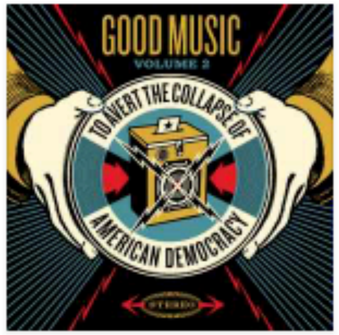

Number of Overpayments by top 20 countries
Number of Overpayments
100000
80000
60000
40000
20000
0
United States
United Kingdom
Germany
Australia
Canada
France
Japan
Netherlands
Switzerland
Italy
Spain
Russian Federation
Belgium
Sweden
Ireland
Poland
New Zealand
Finland
Norway
Austria
Country


Number of Overpayments by Country
Number of Overpayments
0
200
400
600
800
Mexico
Brazil
China
India
Country


Top 20 Countries by Total Overpayment (USD)
Total Overpayment (USD)
70000
60000
50000
40000
30000
20000
10000
0
United States
United Kingdom
Germany
Japan
Australia
Canada
France
Netherlands
Switzerland
Russian Federation
Italy
Belgium
Spain
Sweden
Poland
Ireland
Finland
New Zealand
Denmark
Norway
Country


Total Overpayment by Media Type
Total Overpayment (USD)
120000
100000
80000
60000
40000
20000
0
digital
Vinyl
CD
bundle
Tape
Physical media
Media Type


Top 20 Artists by Total Overpayment (USD)
Total Overpayment (USD)
0
500
1000
Various Artists
□□□(Camellia)
MIQEDEM
James Coates
Celer
Fleet Foxes
Jeff Rosenstock
Micah Frank
Bucketheadland
haircuts for men
RAW
Various Artists Working to Avert the Collapse of American Democracy
Deerhoof
SAULT
Jay Diggs
Mogwai
Cut Chemist
Skáphe
DAN TERMINUS
the garages
Artist Name



Various – Good Music To Avert The Collapse Of American Democracy (Volume 2)

Label:	Good Music (20) – none
Series:	Good Music To Avert The Collapse Of American Democracy – 2
Format:	77 x File, MP3, Compilation, *320 kbps*
Country:	
Released:	Oct 2, 2020
Genre:	Electronic, Hip Hop, Rock, Funk / Soul, Folk, World, & Country
Style:	Alternative Rock

Tracklist

Hide Credits

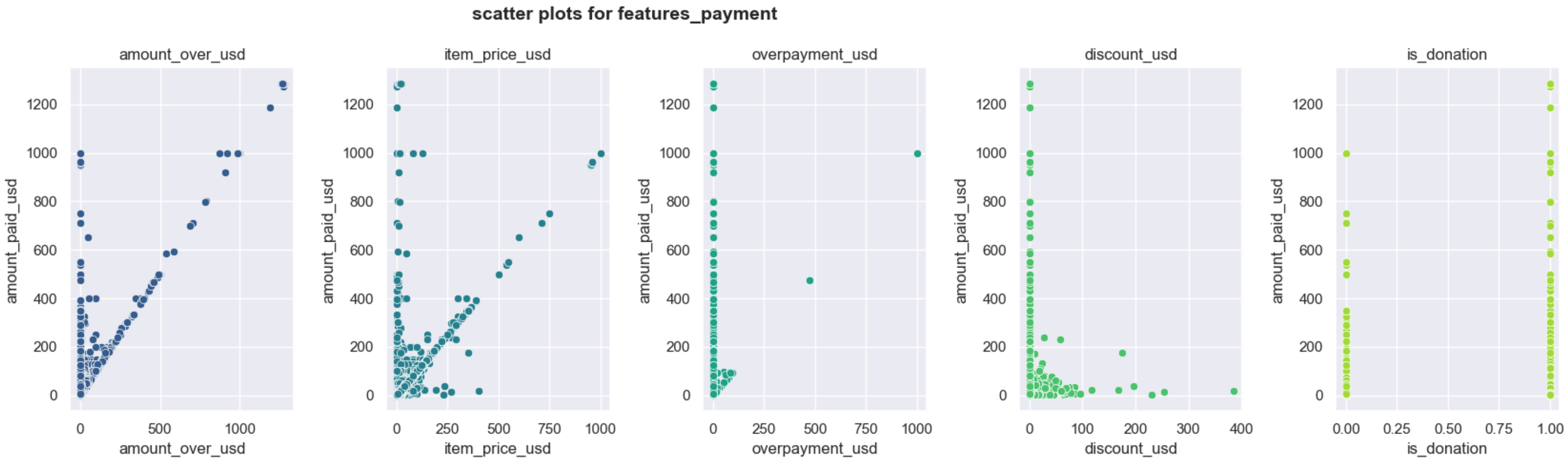
1	David Byrne – People Tell Me	2:54
2	Pearl Jam – Get It Back	3:41
3	Little Dragon – Night Shift	4:11
4	The Postal Service – We Will Become Silhouettes (Live From Berkeley, CA 2013)	5:37
5	Cold War Kids – Almost A Crime	3:11
6	Black Pumas – Colors (Live)	3:28
7	Mark Ronson & Ilsey Juber – No Time To Die	4:07
8	Guided By Voices – Game Of Pricks (Live From The Teragram Ballroom, LA On 12/31/19)	2:07
9	Phoenix – No Woman	2:40
10	Yola (4) – To Be Young, Gifted And Black	3:51

Payment related features

```
df[features_payment].sample(10)
```

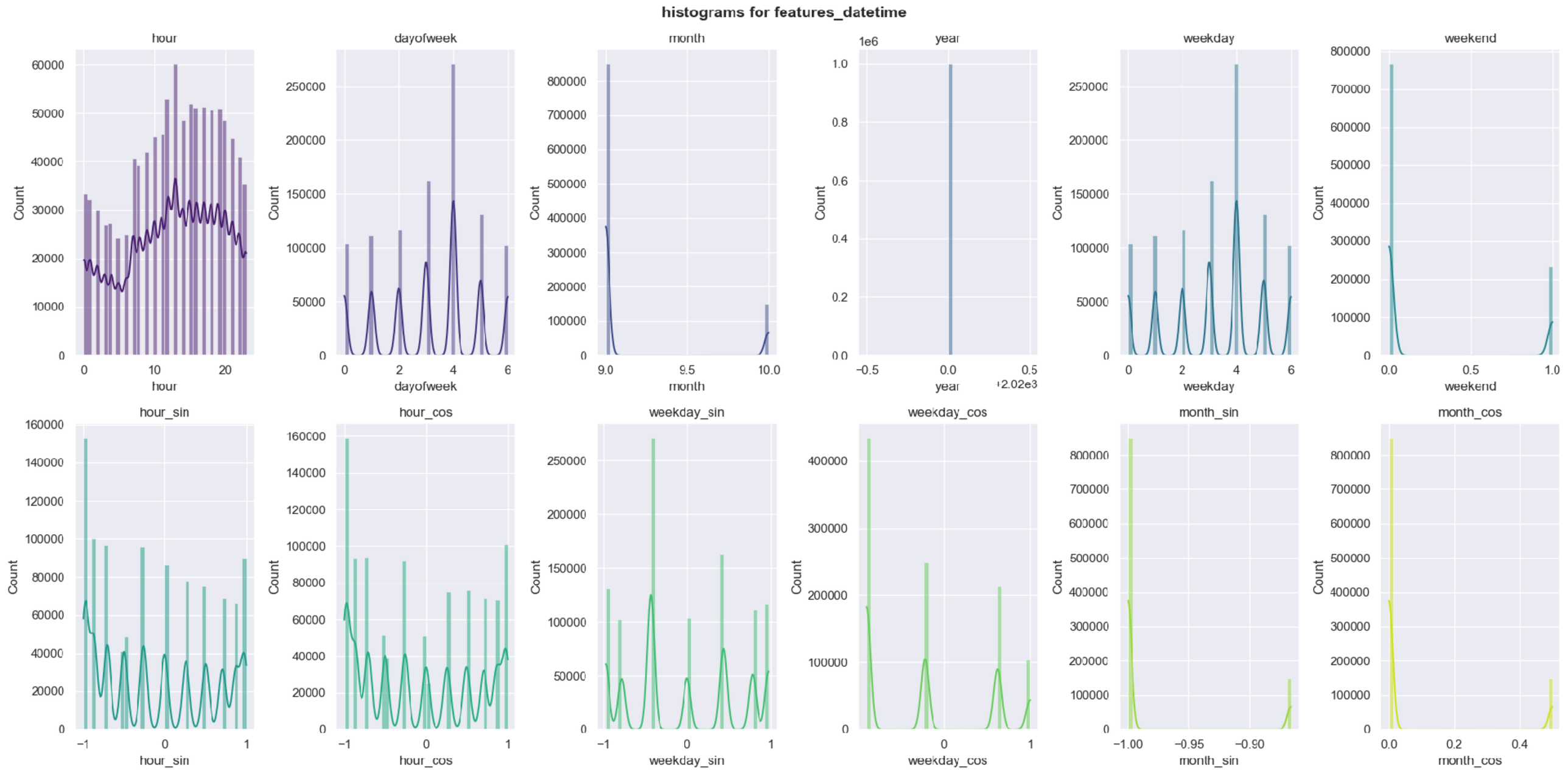
✓ 0.0s

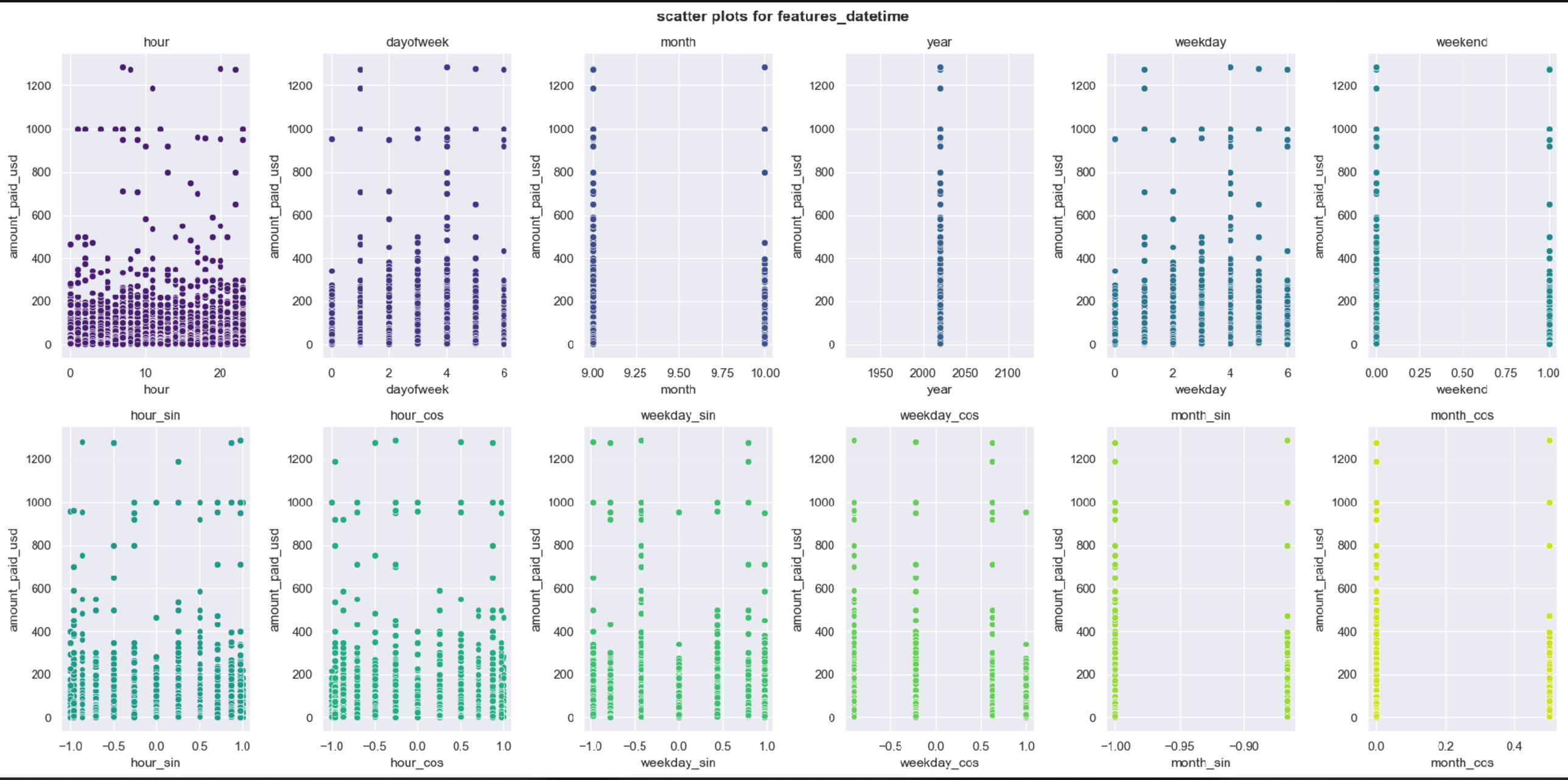
	amount_paid_usd	amount_over_usd	item_price_usd	overpayment_usd	discount_usd	is_donation
421852	11.86	0.00	10.674	1.186000e+00	0.0	1
211931	1.00	0.00	0.000	1.000000e+00	0.0	1
116254	5.92	0.00	5.920	0.000000e+00	0.0	0
409338	25.00	17.01	7.990	2.288818e-07	0.0	1
817142	0.51	0.00	0.000	5.100000e-01	0.0	1
953363	10.28	0.00	10.280	2.944813e-07	0.0	1
227536	7.30	0.00	7.300	0.000000e+00	0.0	0
705140	5.62	0.00	5.620	0.000000e+00	0.0	0
601663	15.00	0.00	13.990	1.010000e+00	0.0	1
18076	4.74	0.00	4.740	0.000000e+00	0.0	0


scatter plots for features_payment
amount_over_usd
item_price_usd
overpayment_usd
discount_usd
is_donation
amount_paid_usd
0
200
400
600
800
1000
1200
0
500
1000
0
250
500
750
1000
0
100
200
300
400
0.00
0.25
0.50
0.75
1.00

Datetime encoding

	hour_sin	hour_cos	weekday_sin	weekday_cos	month_sin	month_cos	is_weekend	is_weekday
406602	-1.000000	-1.836970e-16	-0.974928	-0.222521	-1.000000	-1.836970e-16	1	1
778107	0.258819	9.659258e-01	0.781831	0.623490	-1.000000	-1.836970e-16	0	1
684732	-0.500000	-8.660254e-01	-0.974928	-0.222521	-1.000000	-1.836970e-16	1	1
647883	-0.965926	2.588190e-01	-0.433884	-0.900969	-1.000000	-1.836970e-16	0	1
875331	-0.866025	-5.000000e-01	0.433884	-0.900969	-0.866025	5.000000e-01	0	1
840240	-0.965926	2.588190e-01	0.974928	-0.222521	-1.000000	-1.836970e-16	0	1
563945	0.500000	8.660254e-01	0.433884	-0.900969	-1.000000	-1.836970e-16	0	1
650660	-0.866025	5.000000e-01	-0.433884	-0.900969	-1.000000	-1.836970e-16	0	1
472939	-0.965926	-2.588190e-01	0.000000	1.000000	-1.000000	-1.836970e-16	0	1
913288	0.965926	-2.588190e-01	-0.433884	-0.900969	-0.866025	5.000000e-01	0	1


histograms for features_datetime
hour
dayofweek
month
year
weekday
weekend
hour_sin
hour_cos
weekday_sin
weekday_cos
month_sin
month_cos
Count
1e6
+2.02e3


scatter plots for features_datetime
hour
dayofweek
month
year
weekday
weekend
hour_sin
hour_cos
weekday_sin
weekday_cos
month_sin
month_ccs
amount_paid_usd

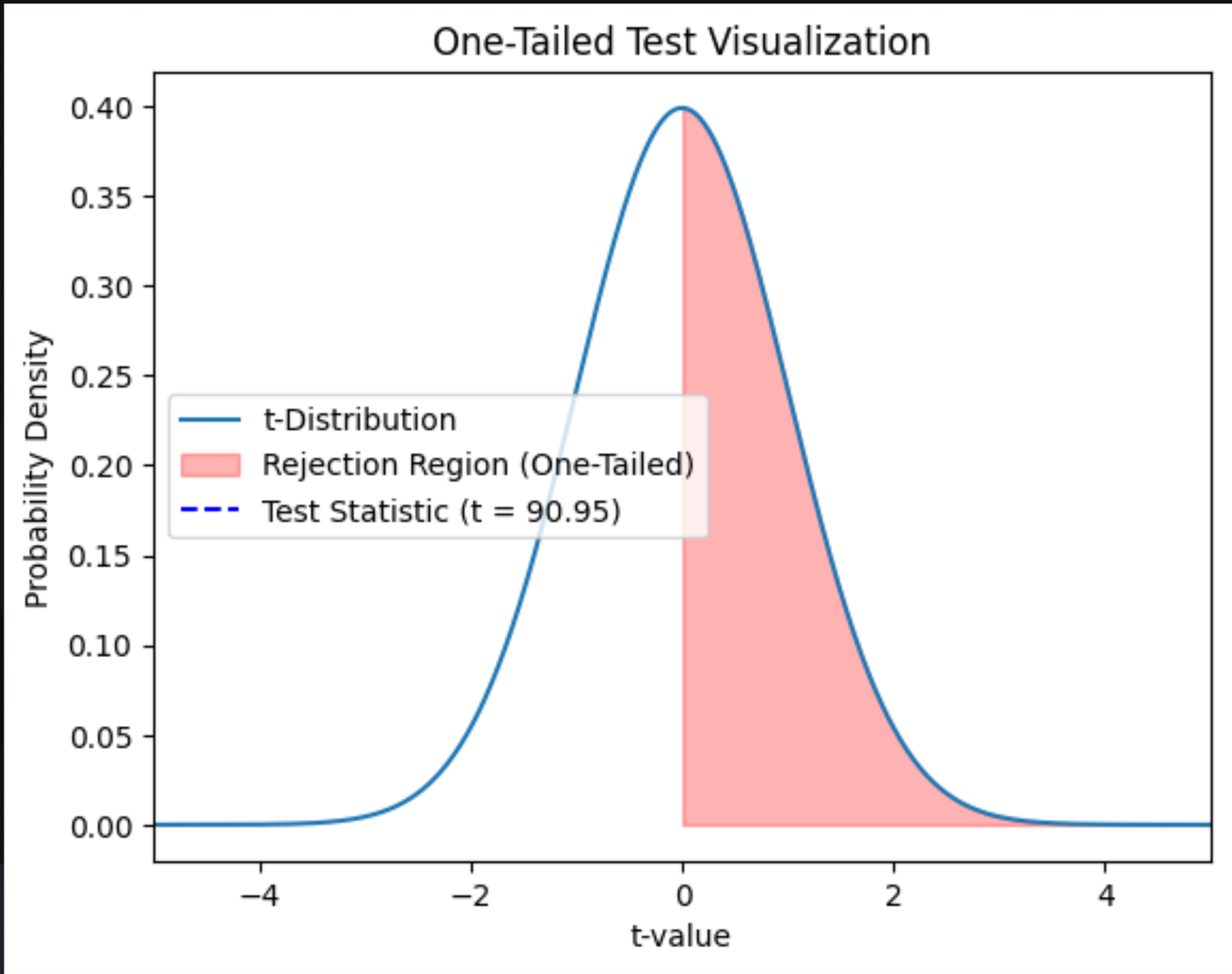
Hypothesis testing

Friday sales

One-tailed T-test

- H0 = "Sales on Bandcamp are not different on Fridays than on any other days of the week."
- H1 = "Sales on Bandcamp are higher on Fridays."

- Test Statistic (t): 90.95
- P-Value: 0.0000
- Reject the Null Hypothesis



90.95%

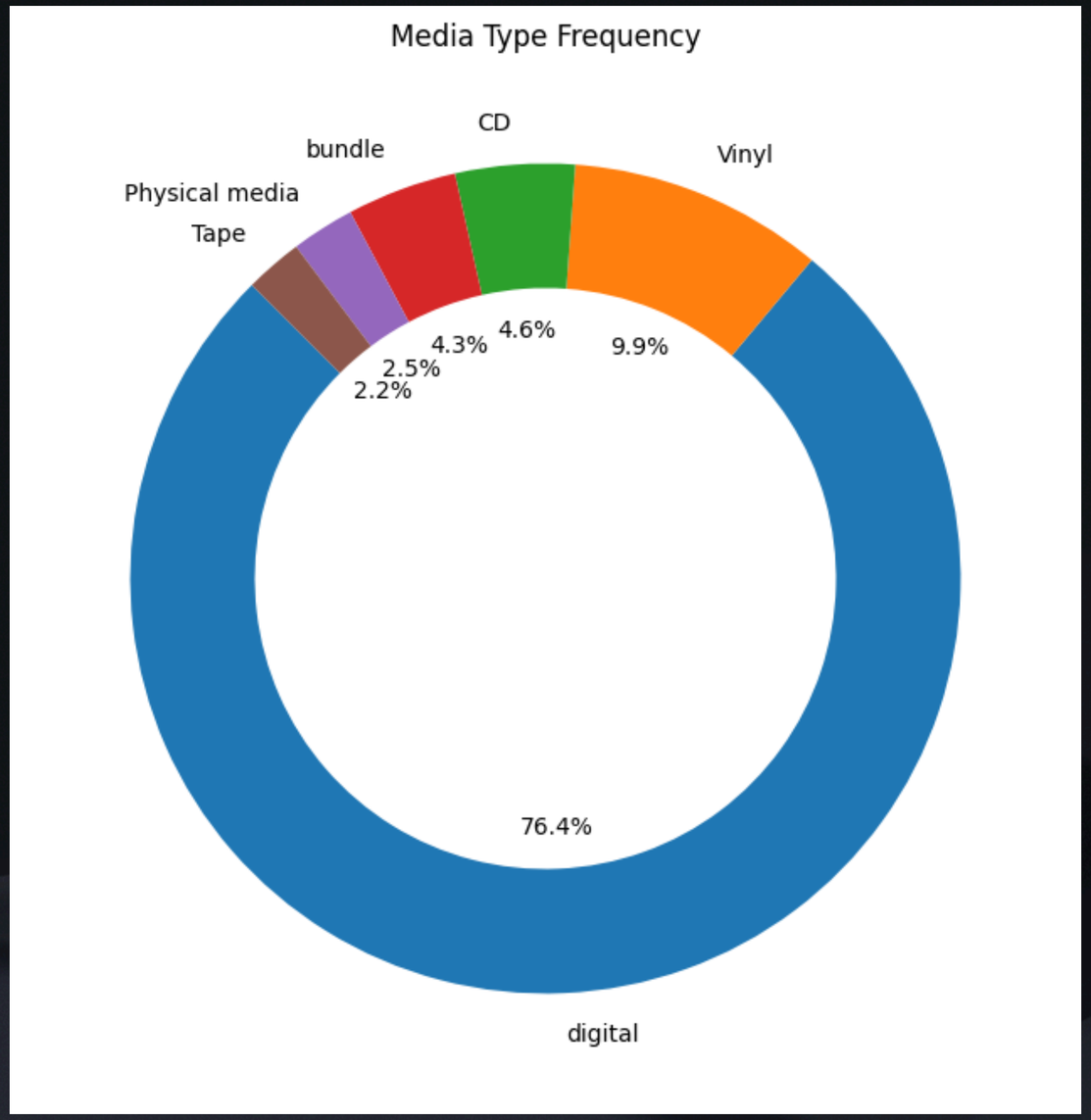
Higher sales on Fridays

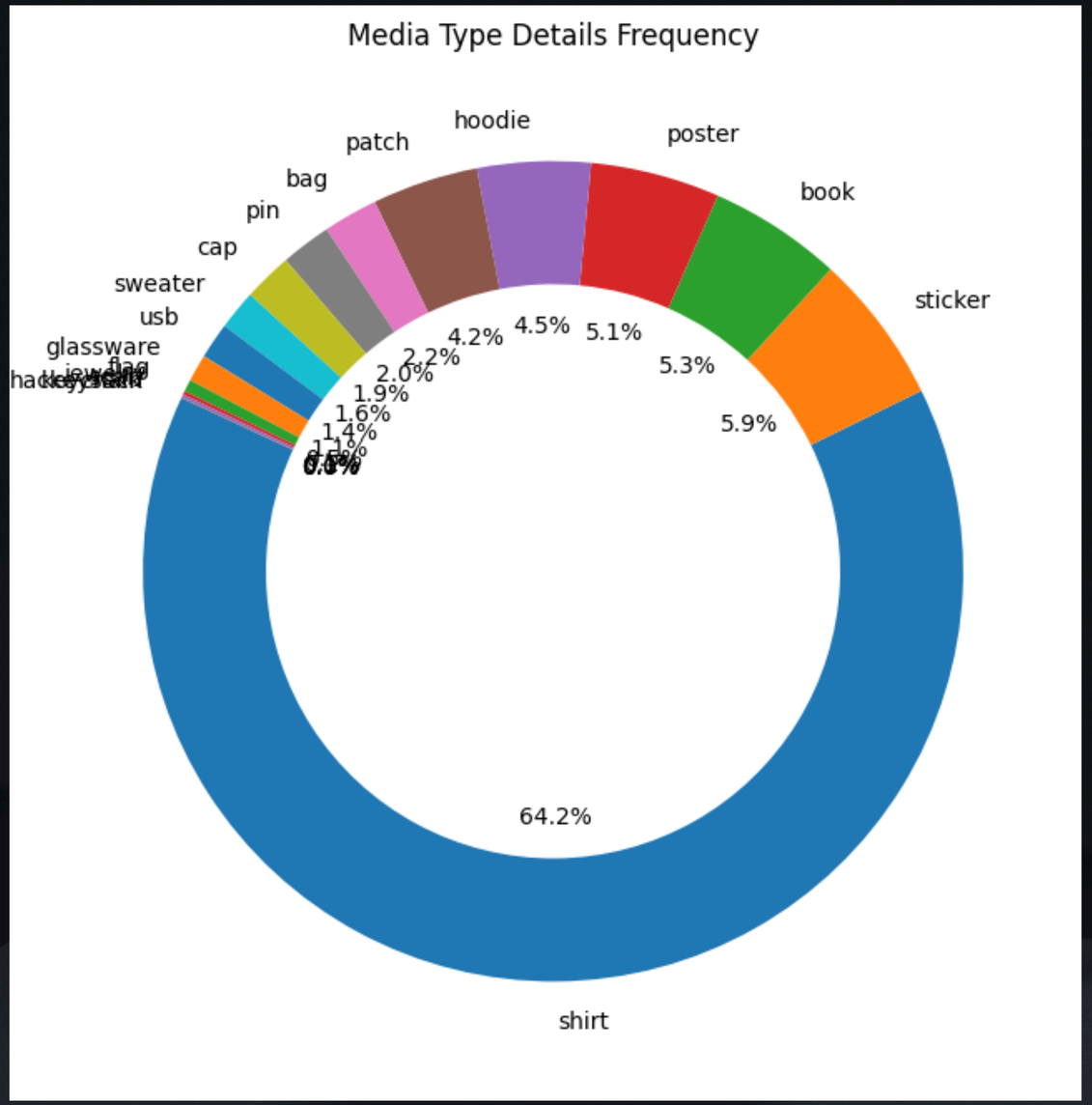
Media type analysis

Case reference table

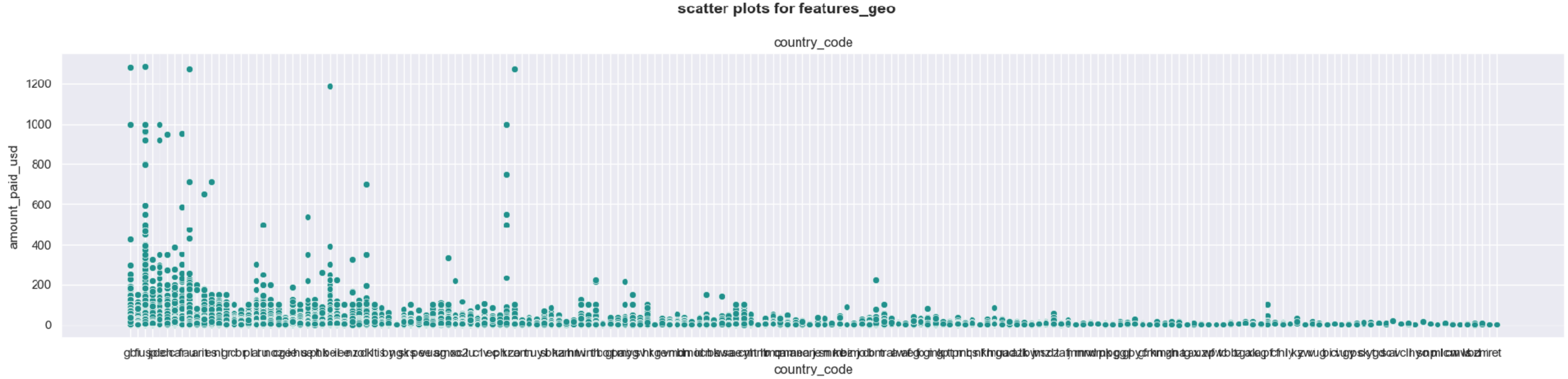
After exploring 16 possible combinations total, it is identified that only 5 of them actually contain data:

Comination	Product	Transformation notes
Combination: ('a', 'a')	digital album only	Vynil is usually sold with digital included, should be summed up
Combination: ('t', 't')	digital single track	can be united with digital albums and saved as 'digital'
Combination: ('p', 'a')	CD or Vinyl	parse text from 'item_description' if not empty
Combination: ('p', 'p')	Merch or Bundle with CD / Vinyl	parse 'item_description', keep CD/Vinyl and drop all merch
Combination: ('b', 'missing')	digital, other	parse 'item_description', verify that it is always 'full digital discography'


Media Type Frequency
CD
bundle
Vinyl
Physical media
Tape
4.6%
4.3%
9.9%
2.5%
2.2%
76.4%
digital


Media Type Details Frequency
hoodie
patch
poster
bag
book
pin
cap
sticker
sweater
usb
glassware
4.2%
4.5%
5.1%
2.2%
2.0%
5.3%
1.9%
1.6%
1.4%
5.9%
64.2%
shirt

Geo encoding


scatter plots for features_geo
country_code
amount_paid_usd
1200
1000
800
600
400
200
0
country_code

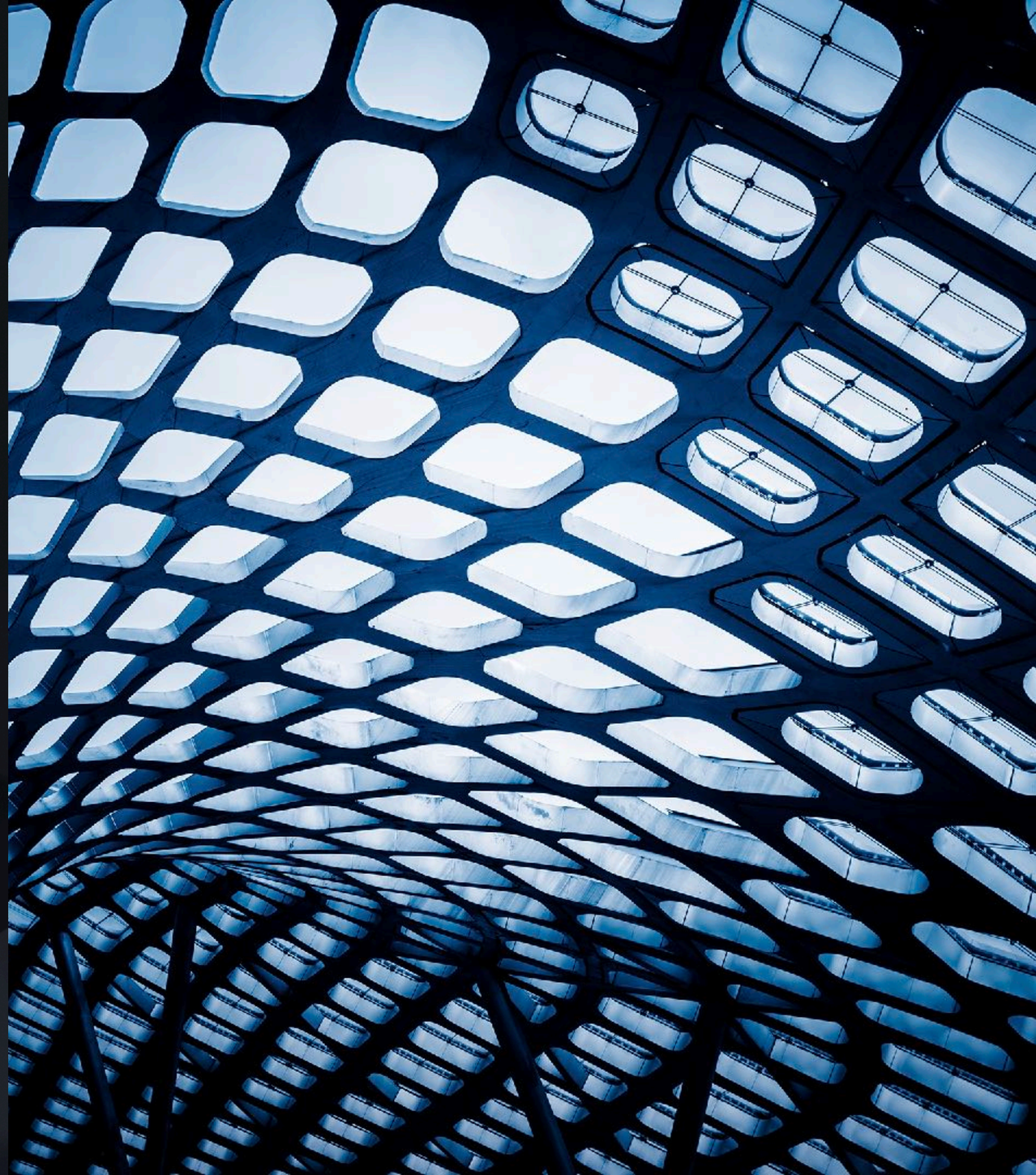
Configuring models

Linear Regression

With raw numeric features

```
['utc_date',
 'item_price',
 'art_id',
 'amount_paid',
 'releases',
 'amount_paid_usd',
 'package_image_id',
 'addl_count']
```

	test_size	random_state	R2	MAE	RMSE	MSE
LR_numeric_features_raw_ts0.1_rs15	0.1	15.0	1.0	0.0	0.0001	0.0
LR_numeric_features_raw_ts0.1_rs42	0.1	42.0	1.0	0.0	0.0001	0.0
LR_numeric_features_raw_ts0.1_rs100	0.1	100.0	1.0	0.0	0.0001	0.0
LR_numeric_features_raw_ts0.2_rs15	0.2	15.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.2_rs42	0.2	42.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.2_rs100	0.2	100.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.3_rs15	0.3	15.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.3_rs42	0.3	42.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.3_rs100	0.3	100.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.4_rs15	0.4	15.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.4_rs42	0.4	42.0	1.0	0.0	0.0000	0.0
LR_numeric_features_raw_ts0.4_rs100	0.4	100.0	1.0	0.0	0.0000	0.0



Feature-tuned + hyper parameter testing

```
blend_geo_product = features_geo_encoded + features_product_encoded
blend_geo_payment = features_geo_encoded + features_payment
blend_geo_datetime = features_geo_encoded + features_datetime
blend_product_payment = features_product_encoded + features_payment
blend_product_datetime = features_product_encoded + features_datetime
blend_payment_datetime = features_payment + features_datetime
blend_geo_product_payment = features_geo_encoded + features_product_encoded + features_payment
blend_geo_product_datetime = features_geo_encoded + features_product_encoded + features_datetime
blend_geo_payment_datetime = features_geo_encoded + features_payment + features_datetime
blend_product_payment_datetime = features_product_encoded + features_payment + features_datetime
blend_geo_product_payment_datetime = features_geo_encoded + features_product_encoded + features_payment + features_datetime
```

	test_size	random_state	R2	MAE	RMSE	MSE
LR_geo_product_ts0.1_rs15	0.1	15.0	0.4957	3.8826	7.7818	60.5563
LR_geo_product_datetime_ts0.1_rs15	0.1	15.0	0.4956	3.8806	7.7820	60.5592
LR_all_ts0.1_rs15	0.1	15.0	0.4956	3.8806	7.7820	60.5592
LR_geo_product_payment_datetime_ts0.1_rs15	0.1	15.0	0.4956	3.8806	7.7820	60.5592
LR_geo_product_payment_ts0.1_rs15	0.1	15.0	0.4956	3.8806	7.7820	60.5592
...	...	...	...	...	...	...
LR_payment_datetime_ts0.4_rs15	0.4	15.0	0.0088	6.7876	11.5607	133.6495
LR_payment_datetime_ts0.4_rs100	0.4	100.0	0.0088	6.8037	11.9673	143.2159
LR_payment_datetime_ts0.2_rs15	0.2	15.0	0.0086	6.7685	11.4977	132.1962
LR_payment_datetime_ts0.3_rs15	0.3	15.0	0.0083	6.7876	11.7402	137.8332
LR_payment_datetime_ts0.4_rs42	0.4	42.0	0.0082	6.8113	12.6112	159.0426

144 rows × 6 columns

```
test_size: 0.1
random_state: 15
R2: 0.49565228232063796
MAE: 3.8825756483756377
RMSE: 7.781792555837239
MSE: 60.55629538208386
```

Random Forest REGRESSOR

Base model

Runtime 1 min

```
test_size: 0.3
random_state: 15
R2: 0.513371077370987
MAE: 3.1795683615445007
RMSE: 8.223994759698543
MSE: 67.6340898075491
n_estimators: 10
```

Second model = Best model

Runtime 10 min

	test_size	random_state	R2	MAE	RMSE	MSE	n_estimators
LR_geo_product_ts0.1_rs15_ne100	0.1	15.0	0.6224	2.7557	6.733	45.3332	100.0

Other models

Runtime 48 min

	test_size	random_state	R2	MAE	RMSE	MSE	n_estimators
LR_geo_product_ts0.1_rs15_ne200	0.1	15.0	0.6199	2.7548	6.756	45.6430	200.0
LR_all_ts0.1_rs15_ne200	0.1	15.0	0.5673	2.9463	7.208	51.9556	200.0

Regressors comparison

amount_paid, $	R2 Score	RMSE	MAE
Linear Regression	49 %	$ 7.78	$ 3.88
Random Forest	62 %	$ 6.73	$ 2.75

Random Forest CLASSIFIER

Will there be a donation?

- Predict customer behavior:
  - Voluntarily paying on top of the minimum price.
- Check for “is_donation” 0 or 1 value.
- Grid search results:
  - {'max_depth': 20, 'min_samples_split': 10}
  - Best score: 0.66342

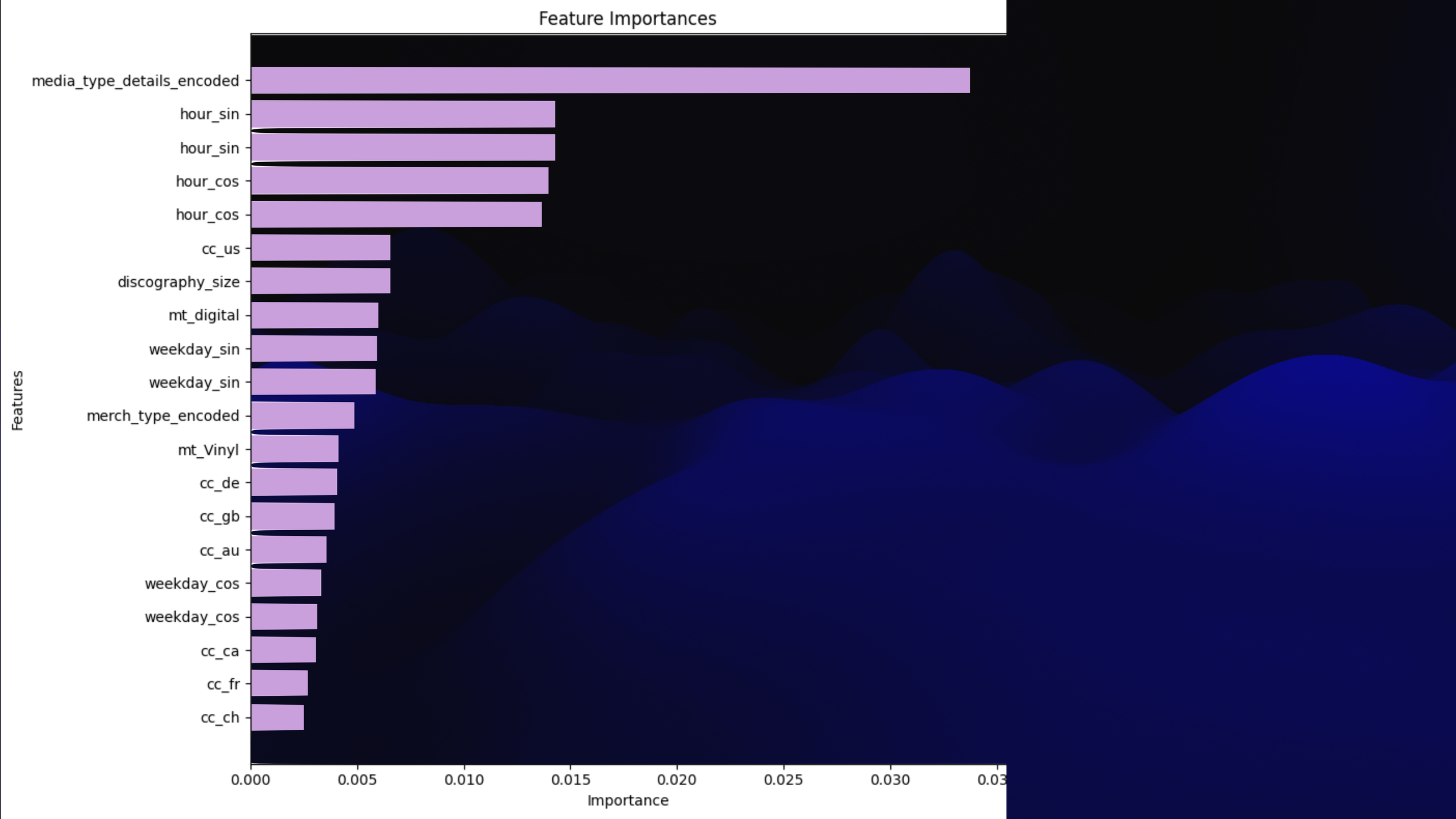
```python
target_variable_extra = "amount_over_fmt"

# Can I use the data for prediction?

df["amount_over_fmt"].apply(type).value_counts()
```

```
amount_over_fmt
<class 'float'>    880867
<class 'str'>      119133
Name: count, dtype: int64
```

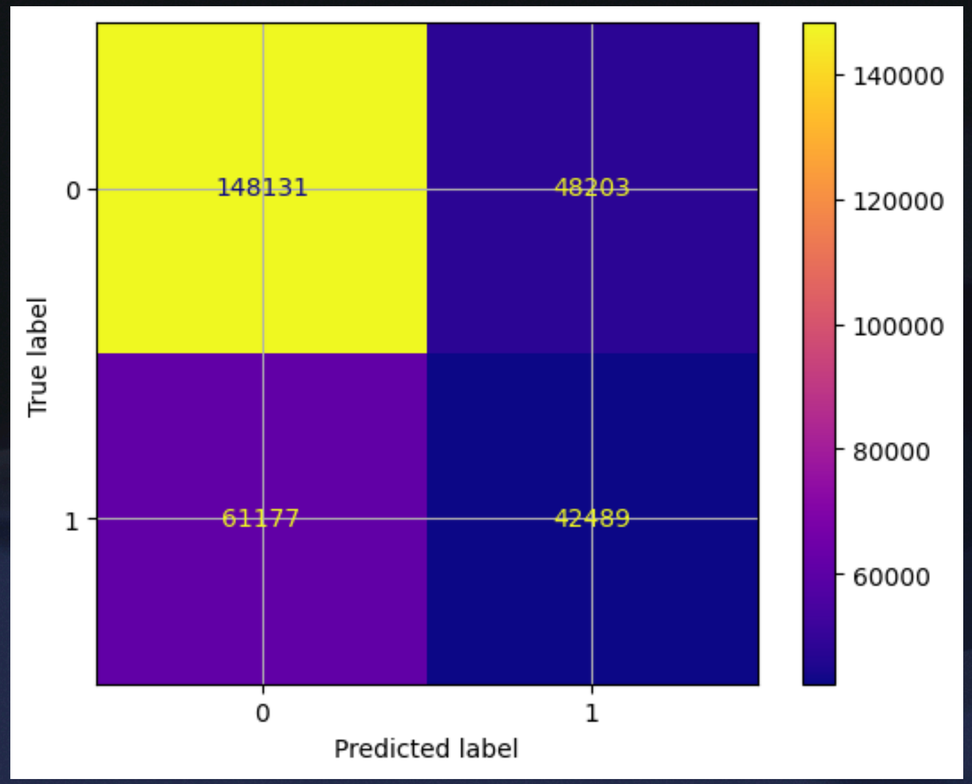
- Payment analysis
- Feature engineering

Modelling strategy:

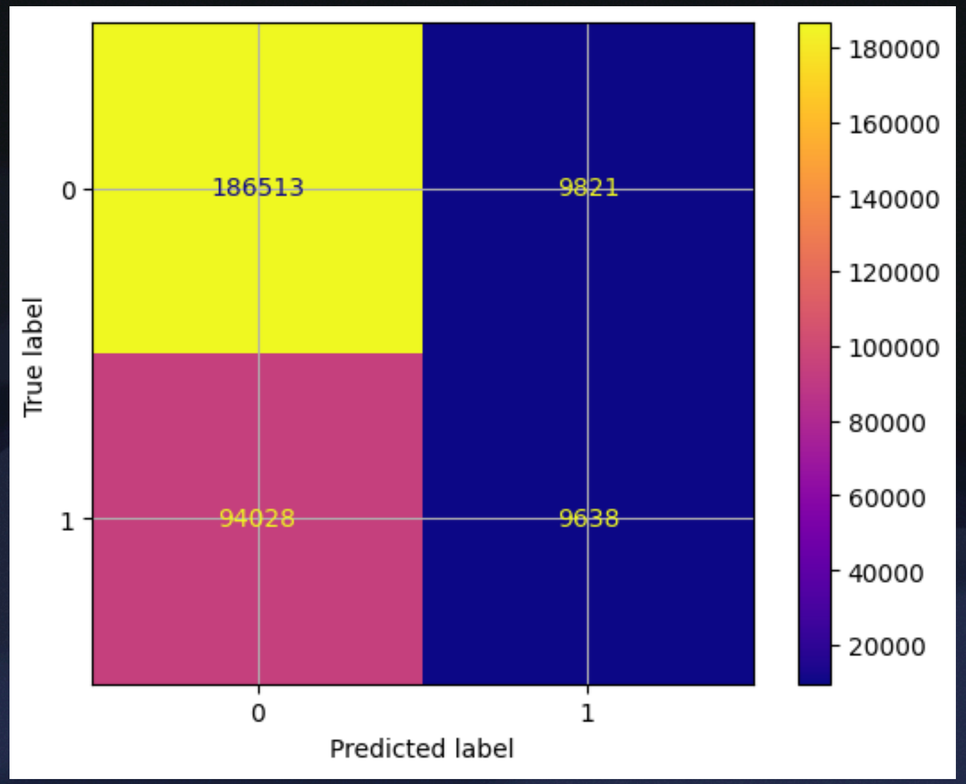
- Column `is_donation` with values 0 or 1.
  - What to consider as donation case true / false from `overpayment` and `amount over`?
    - Rule: `amount_over_usd` > 0 OR `overpayment` > 0.
  - Do not include features that directly set the donation flag in the train subdset:
    - `amount_over_usd`, `overpayment`, `amount_paid`.
  - Keep `item_price`, `discount`. Corellated, but not directly.


Feature Importances
media_type_details_encoded
hour_sin
hour_sin
hour_cos
hour_cos
cc_us
discography_size
mt_digital
weekday_sin
weekday_sin
merch_type_encoded
mt_Vinyl
cc_de
cc_gb
cc_au
weekday_cos
weekday_cos
cc_ca
cc_fr
cc_ch
Features
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.03
Importance

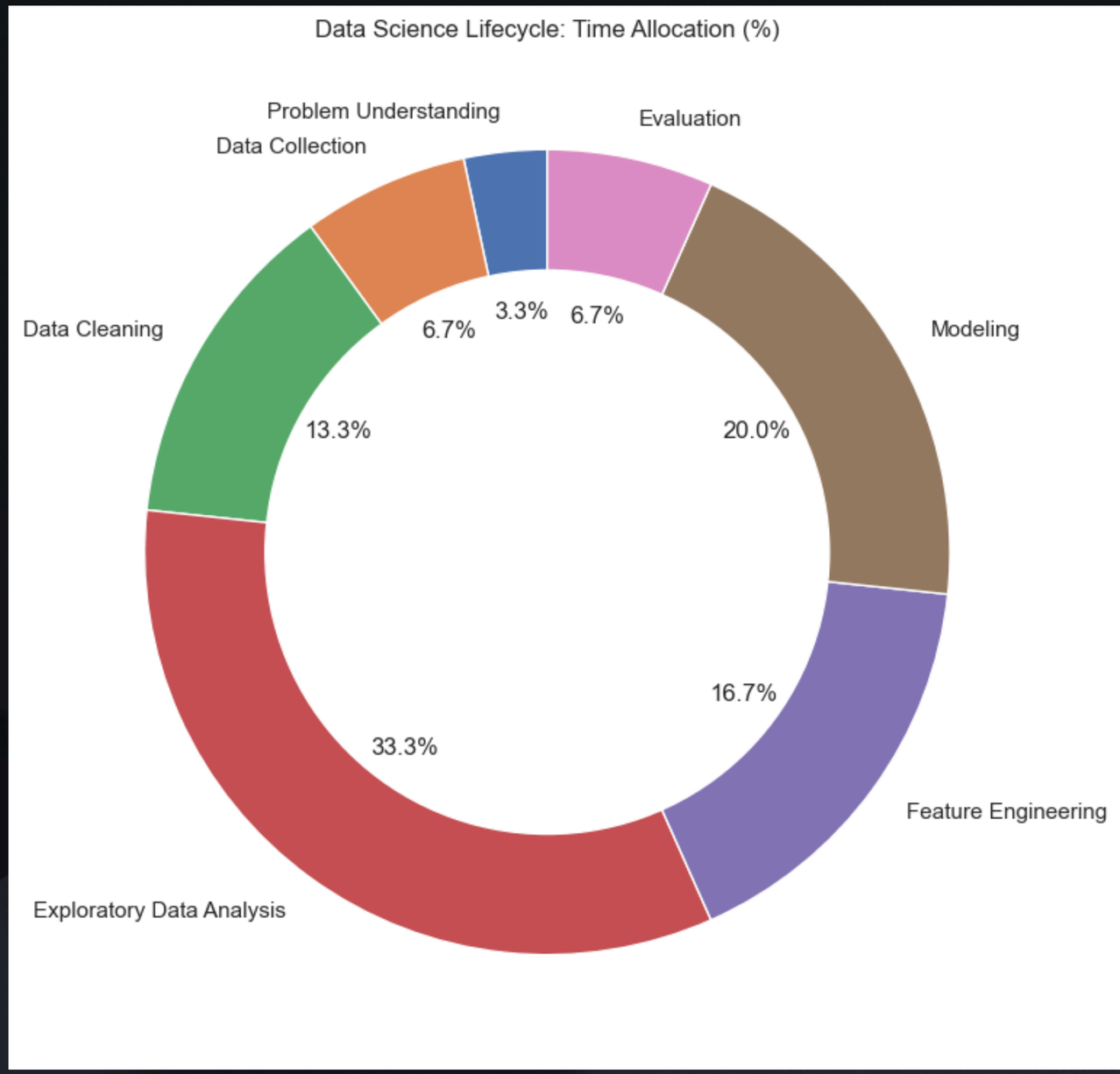
```
accuracy:
 0.6648
class_report:
              precision    recall  f1-score   support

           0       0.67      0.96      0.79    196334
           1       0.58      0.10      0.18    103666

    accuracy                           0.66    300000
   macro avg       0.63      0.53      0.48    300000
weighted avg       0.64      0.66      0.58    300000
```



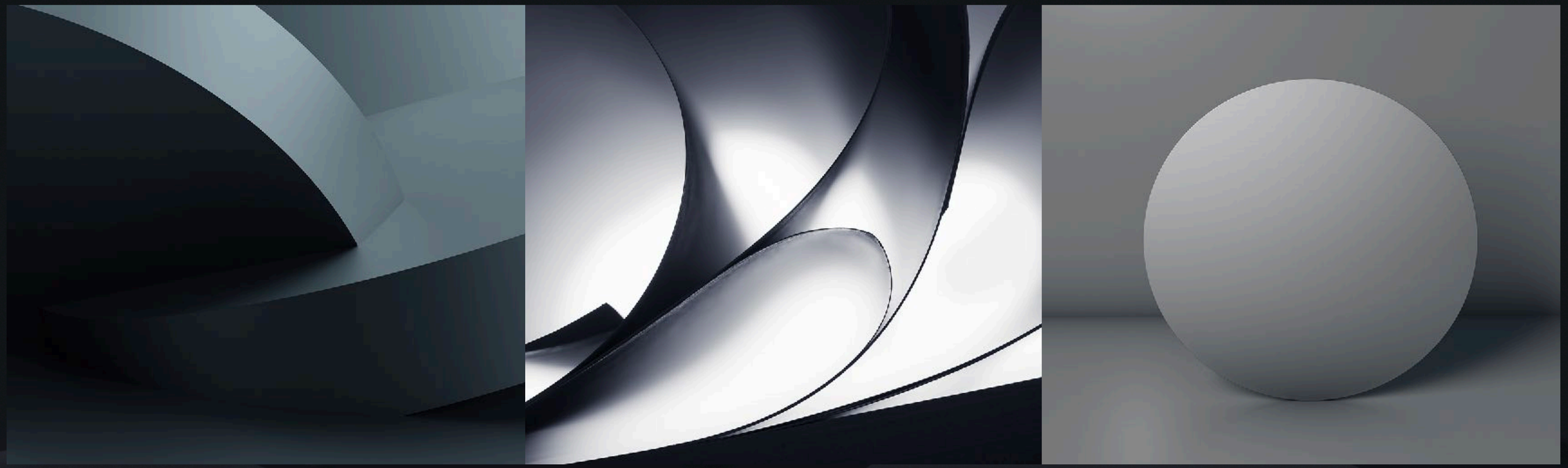

```
accuracy:
 0.6557666666666667
class_report:
              precision    recall  f1-score   support

           0       0.67      0.95      0.78    196334
           1       0.51      0.09      0.16    103666

    accuracy                           0.66    300000
   macro avg       0.59      0.52      0.47    300000
weighted avg       0.61      0.66      0.57    300000
```



Data Science Lifecycle



Questions?



Thank you!