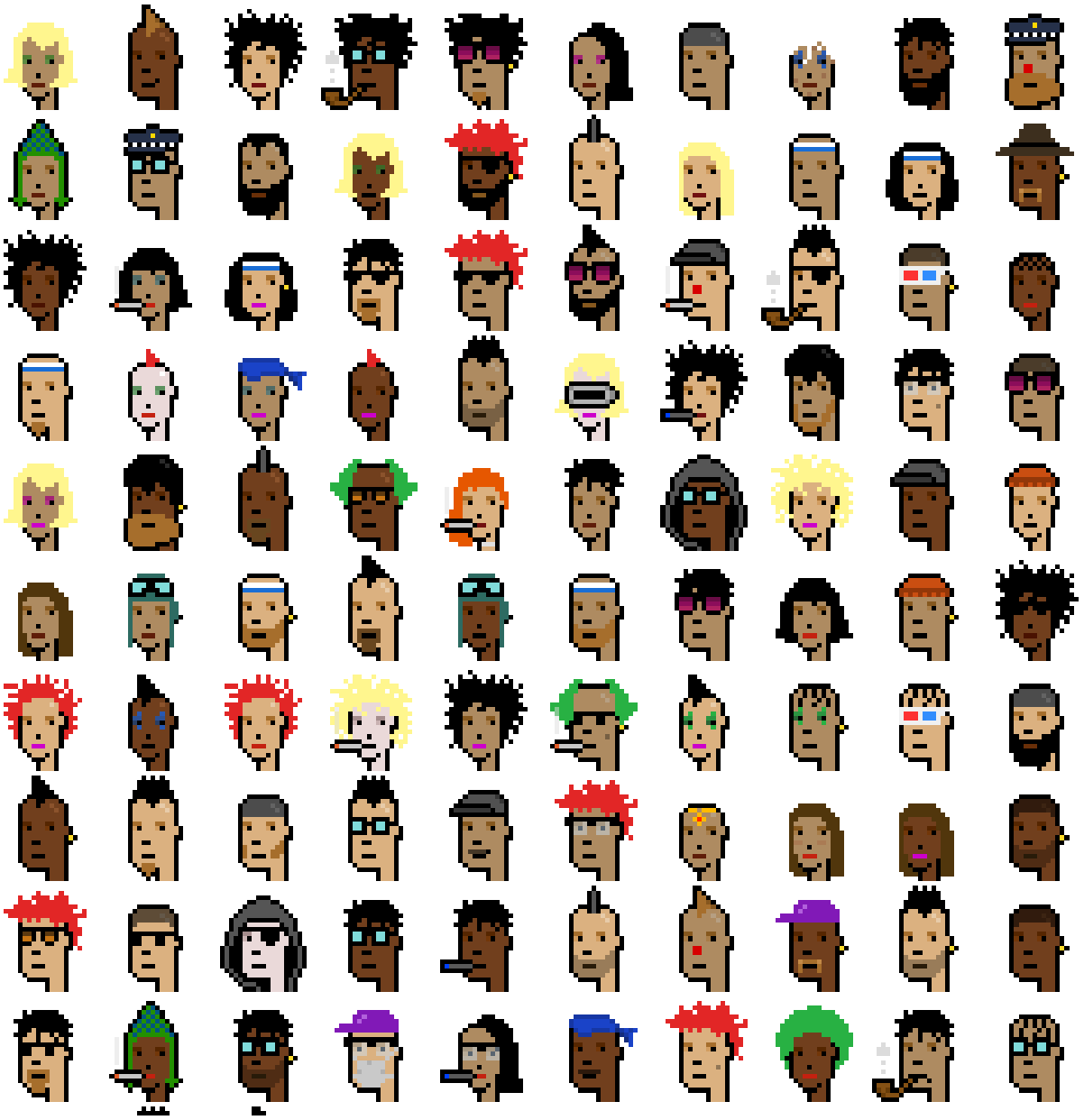

CryptoPunks

Data Science project

IT Academy Barcelona Activa

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Abstract

This paper contains an analysis and machine learning model of Crypto Punks project from Larva Labs available on the non-fungible token market (NFT). This digital art collection stored on the Ethereum blockchain is getting highly popular due to the huge amount of money invested so far.

Data analysis reveals that the original owners gain the most profit and the market is very sensitive to sales made by celebrities and influencers. The prices are not stable and there is no guarantee of liquidity in this NFT project.

The objective is to prove that not all characters are the same and do not have the same price and availability on the market. This hypothesis is studied by comparing types, skins, attributes and prices of the characters.

The paper is divided into three parts. In the first part, data is collected by web scraping and a new relational database is being created with characters, types, skins, attributes and all transactions. In the second part, an exploratory analysis speaks about differences between the characters and seeks to determine one group of characters for further study. In the third part, the machine learning model aims to classify the selected group and find some common patterns.

The result of this research is a reproducible experiment analysing the CryptoPunks market and its economic value and credibility.

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1. Information about CryptoPunks

1.1. What are CryptoPunks

CryptoPunks is a collection of digital art, one of the earliest non-fungible token projects launched in June 2017 by the Larva Labs studio inspired by the London punk scene.[1]

One Cryptopunk is an image with digital signature of property, 24x24 pixels wide with some character in particular. There are male, female, simios, zombies and aliens.

CryptoPunk is an example of NFT - non-fungible token created on Ethereum network. First designs were made manually and the rest by algorithm. Etherum network is open source blockchain with smart contract functionality. Ether is the native cryptocurrency of the platform and is is second only to Bitcoin in market capitalization. [2]

NFT is a unique and non-interchangeable unit of data stored on a digital ledger. There are no two images of CryptoPunks with the same characteristics. This project of Larvalabs started the popular CryptoArt movement.

There are 10,000 unique CryptoPunks all made digitally with the use of blockchain technology from number 0 to 9999.

The total number of punks is definitive and unalterable. This makes it a status symbol, a piece of Internet history. Official ownership of each work is outlined in a contract on the publicly accessible Ethereum blockchain.

1.2. How do CryptoPunks work

The sales can be realized with a Metamask plugin directly on the Larvalabs official website [1] or at other NFT platforms like OpenSea. All available CryptoPunks are visible on the official website.

First, you should have some Ether currency, available on Coinbase, eToro or Gemini. Once you have enough Ether to purchase the Punk you'll need to transfer your funds to an Ethereum wallet.

Second, you'll need to connect a software wallet MetaMask to Larva Lab's website. Then using this platform it is possible to make a bid on CryptoPunk, while paying GAS tax for this transaction. If the seller accepts your bid, the transaction will be processed through Ethereum's blockchain and the NFT will be sent to your Ethereum wallet. The average price paid for a CryptoPunk recently is around $400,000.

Another option is to trade with wrapped CryptoPunks. That means sell or buy converted non standard NFT to token ERC-721. This makes it compatible with markets like OpenSea and Rarible. It's possible to buy a Punk for an indicated price or make and offer.[3]

1.3. Characteristics of CryptoPunks

There are specific attributes of every CryptoPunk. These CryptoPunks attributes are also responsible for making a CryptoPunk rare and increase the value depending on that. A punk can have up to 7 attributes max.

The rarest punk is punk number 8348 with 7 attributes. Only 8 punks do not have any attribute. The number of attributes is equally responsible for determining the value of the CryptoPunks. [4]

1.3.1 Types

Type	**Alien**	**Ape**	**Zombie**	**Female**	**Male**
Total	9	24	88	3840	6039

1.3.2 Skins

Skin	**Alien**	**Ape**	**Zombie**	**Albino**	**Dark**	**Light**	**Mid**
Total	9	24	88	1018	2824	3006	3031

1.3.3 Total number of attributes

Total attributes	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Total	8	333	3560	4501	1420	166	11	1

Some attributes are more special than the others because of the total number of characters having some specific attribute. Total number of characters with specific attribute is a relevant value for the rarest rank of each character.

Some attributes can also be more popular than others based on similarity of that attribute with physical appearance of some celebrity or other external influences.

1.3.4 Attributes

Attribute	Total	Attribute	Total	Attribute	Total
Beanie	44	Medical Mask	175	VR	332
Choker	48	Tassle Hat	178	Cap	351
Pilot Helmet	54	Fedora	186	Small Shades	378
Tiara	55	Police Cap	203	Clown Eyes Green	382
Orange Side	68	Clown Nose	212	Clown Eyes Blue	384
Buck Teeth	78	Smile	238	Headband	406
Welding Goggles	86	Cap Forward	254	Crazy Hair	414
Pigtails	94	Hoodie	259	Knitted Cap	419
Pink With Hat	95	Front Beard Dark	260	Mohawk Dark	429
Top Hat	115	Frown	261	Mohawk	441
Spots	124	Purple Eye Shadow	262	Mohawk Thin	441
Rosy Cheeks	128	Handlebars	263	Frumpy Hair	442
Blonde Short	129	Blue Eye Shadow	266	Wild Hair	447
Wild White Hair	136	Green Eye Shadow	271	Messy Hair	460
Cowboy Hat	142	Vape	272	Eye Patch	461
Wild Blonde	144	Front Beard	273	Stringy Hair	463
Straight Hair Blonde	144	Chinstrap	282	Bandana	481
Big Beard	146	3D Glasses	286	Classic Shades	502
Red Mohawk	147	Luxurious Beard	286	Shadow Beard	526
Half Shaved	147	Mustache	288	Regular Shades	527
Blonde Bob	147	Normal Beard Black	289	Horned Rim Glasses	535
Vampire Hair	147	Normal Beard	292	Big Shades	535
Clown Hair Green	148	Eye Mask	293	Nerd Glasses	572
Straight Hair Dark	148	Goat	295	Black Lipstick	617
Straight Hair	151	Do-rag	300	Mole	644
Silver Chain	156	Shaved Head	300	Purple Lipstick	655
Dark Hair	157	Muttonchops	303	Hot Lipstick	696
Purple Hair	165	Peak Spike	317	Cigarette	961
Gold Chain	169	Pipe	332	Earring	2459

2. Relational database

2.1. Diagram

Database is a collection of all attributes, types and transactions by each punk.[5]

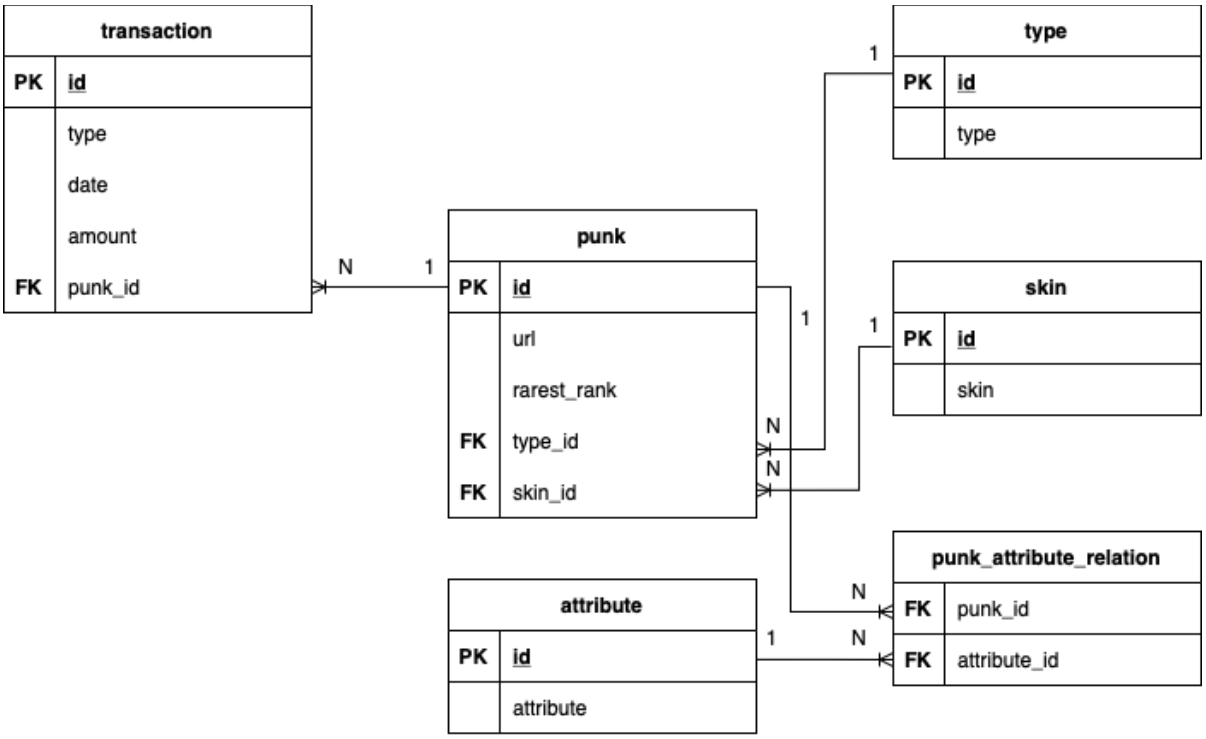

Figure 1. Database relationship diagram

2.2. Tables

Table punk: id: primary key and punk number, url: web page, rarest_rank: rank how unique is it, type_id: foreign key, skin_id: foreign key
Table transaction: id: primary key**,** type: bid, offered, sold, wrapped - get last status, date:date of transaction, amount: price in Ethers - get current price, punk_id: punk number
Table punks_attribute_relation: attribute_id: attribute number, punk_id: punk number
Table attribute: id: primary key, attribute: attribute number
Table skin: id:primary key, skin: skin number
Table type: id:primary key, type: type number

3. Data

3.1. Web scraping

To obtain data, web scraping has been carried out using Python Selenium library. [6] [7]

```
#initiate browser
opts = Options()
opts.headless = True
browser = Firefox(options=opts)
```

```
#loop to fetch all transactions
for i in range(0,10000):
    num = str(i)
    path = 'https://www.larvalabs.com/cryptopunks/details/'+ num
    browser.get(path)
    table = browser.find_element(By.XPATH,'//*[@id="punkHistory"]/div/table/tbody')

    try:
        for element in table.find_elements(By.TAG_NAME, "td"):
            results.append(element.text)
            results.append(num)
    except:
        pass
    time.sleep(0.1)
```

Figure 2. Web scraping code example

3.2. Data cleaning

To facilitate exploratory analysis all data was adapted with regular expression operations and other format changes. Final database contains only the information of true value.

```
df['date'] = df[['year', 'month', 'day']].apply(lambda x: '-'.join(x), axis=1)
df.head(5)
```

	type	7	9	punk_id	id	amount	choice	year	day	mon	month	date
0	Bid	321Ξ ($1.14M)	Sep 01, 2021	0	0	321	False	2021	01	Sep	09	2021-09-01
1	Bid Withdrawn	320Ξ ($1.11M)	Sep 01, 2021	0	1	320	False	2021	01	Sep	09	2021-09-01
2	Bid	320Ξ ($1.1M)	Sep 01, 2021	0	2	320	False	2021	01	Sep	09	2021-09-01
3	Bid Withdrawn	263Ξ ($904,481)	Sep 01, 2021	0	3	263	False	2021	01	Sep	09	2021-09-01
4	Bid	263Ξ ($849,714)	Aug 29, 2021	0	4	263	False	2021	29	Aug	08	2021-08-29

Figure 3. Data processing code example

3.3. Database

Cleaned data inserted to local SQL server, use of PyMySQL Python library.

```
cursor.execute("DROP TABLE IF EXISTS transaction")

cursor.execute("""CREATE TABLE transaction
                (id INT PRIMARY KEY,
                 type VARCHAR(255),
                 date DATE,
                 amount FLOAT,
                 punk_id INT)""")
cursor.execute("SHOW TABLES")
for x in cursor:
    print(x)
```

```
('attribute',)
('punk',)
('punk_attribute_relation',)
('skin',)
('transaction',)
('type',)
```

```
sql = "INSERT INTO transaction (id, type, date, amount, punk_id) VALUES (%s,%s,%s,%s,%s)"

#tuple and than list
df3['all'] = df3[['id','type','date','amount','punk_id']].apply(tuple, axis=1)
val = list(df3['all'])

cursor.executemany(sql, val)
connection.commit()
print(cursor.rowcount, "record inserted")
```

```
177692 record inserted
```

Figure 4. Data inserting code example

```
try:
    query = """SELECT transaction.type, transaction.date, transaction.amount, transaction.punk_id,
    punk.type_id, punk.skin_id
    FROM transaction
    INNER JOIN punk ON punk.id=transaction.punk_id;"""
    df = pd.read_sql(query,connection)
except Exception as e:
    cursor.close()
    print(str(e))
```

```
df.head()
```

	type	date	amount	punk_id	type_id	skin_id
0	Bid	2021-09-01	321.0	0	3	6
1	Bid Withdrawn	2021-09-01	320.0	0	3	6
2	Bid	2021-09-01	320.0	0	3	6
3	Bid Withdrawn	2021-09-01	263.0	0	3	6
4	Bid	2021-08-29	263.0	0	3	6

Figure 5. SQL query code example

4. Exploratory analysis

4.1. General insights - characteristics

4.1.1 Distribution of punks by type

Amount of punks by each type is important because it might influence the ranking and price. Very low numbers of some types would explain high sales in these groups.

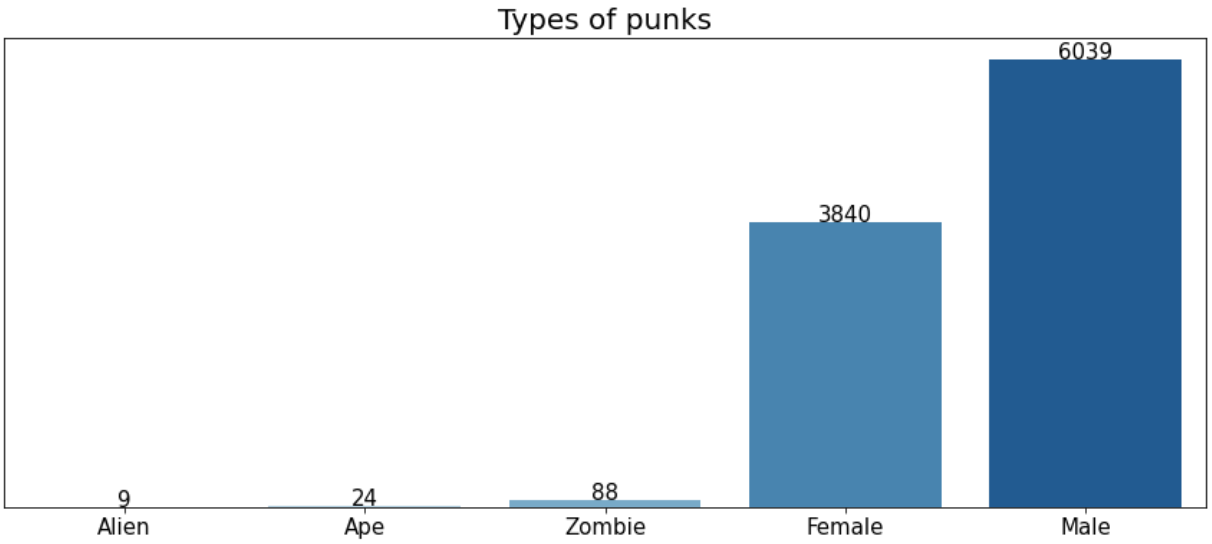

Figure 6. Total amount of punk types

4.1.2 Distribution of punks by skin

Skin type in case of Alien, Ape and Zombie is the same as punk type. In case of male and female types we can observe variation between Albino, Dark, Light and Mid skin color.

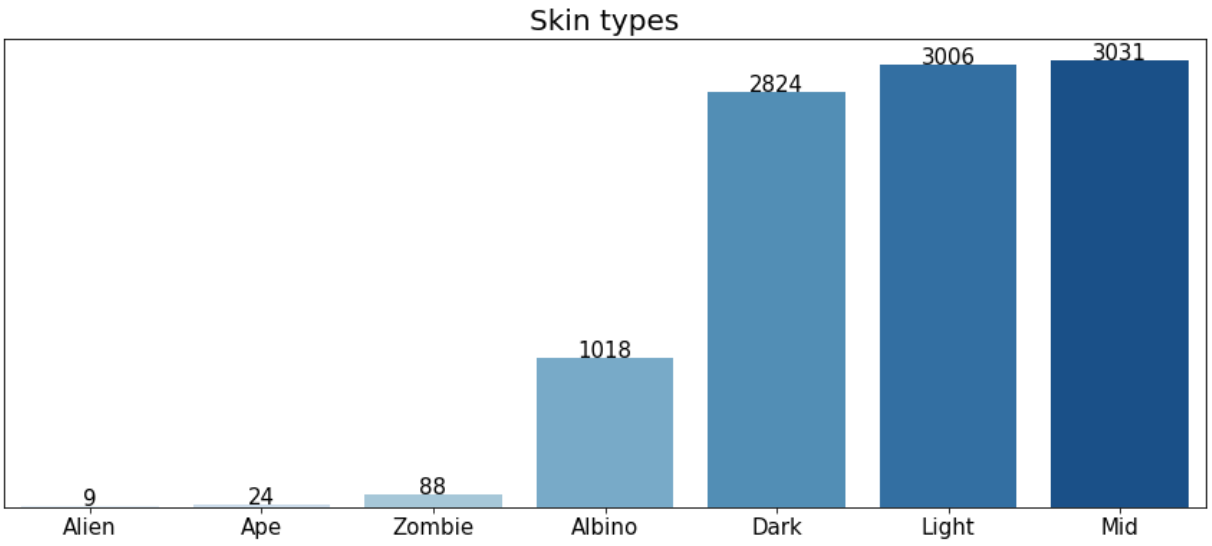

Figure 7. Total amount of skin types

4.1.3 Distribution of punks by attribute

Number of attributes vary from 0 to 7. The groups with the highest total number of punks are these with 2, 3 and 4 attributes.

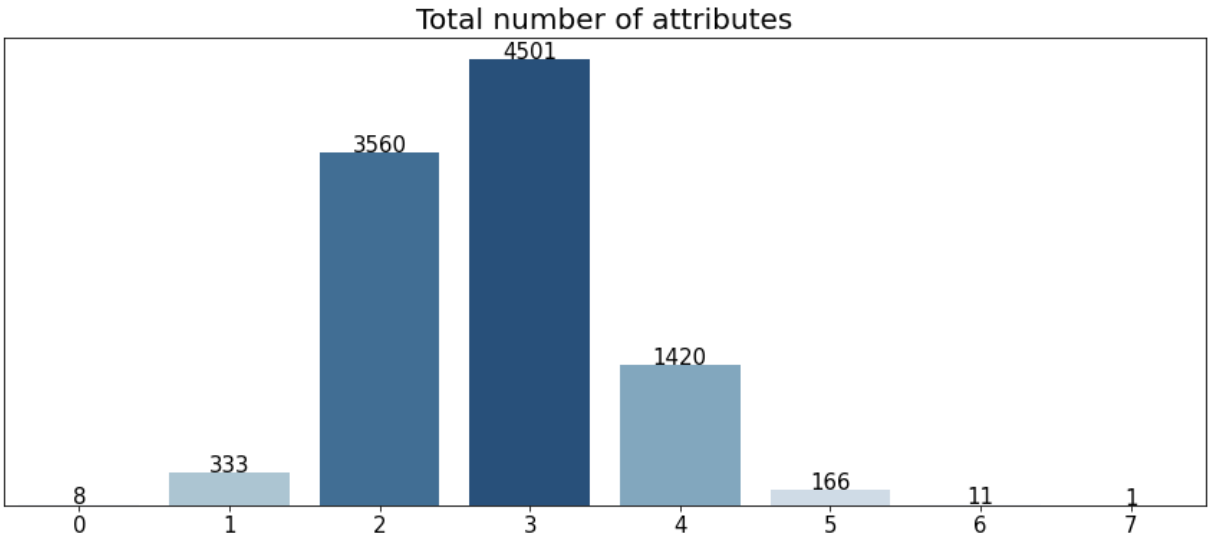

Figure 8. Total amount of punks by number of attributes

4.1.4 Average price of one punk character by type

The actual price of each punk was considered as the average of the last sold amount. Some punks have not been sold ever. In this case the price was considered as 0 because there is no proof of somebody paying any amount of Ethers. Prices of the Aliens and Apes group were collected also manually from the official website [8] with the purpose of checking if the process of web scraping was successful. The group of Aliens, apes and Zombies are the most valuable. The interesting thing is that the average price of the Female group is lower than Male, however this group has a lower total amount.

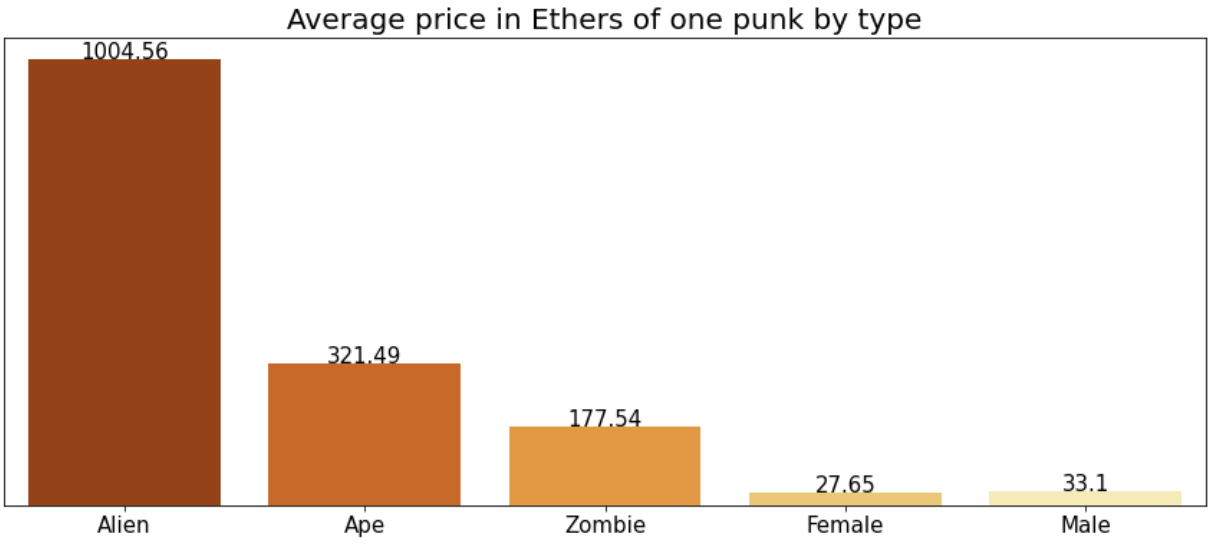

Figure 9. Average price by punk type

4.1.5 Average price of one punk character by skin

The actual price of each punk was considered as the average of the last sold amount. There is almost no difference between Albino, Dark, Light and Mid group. Alien, Ape and Zombie are the most expensive.

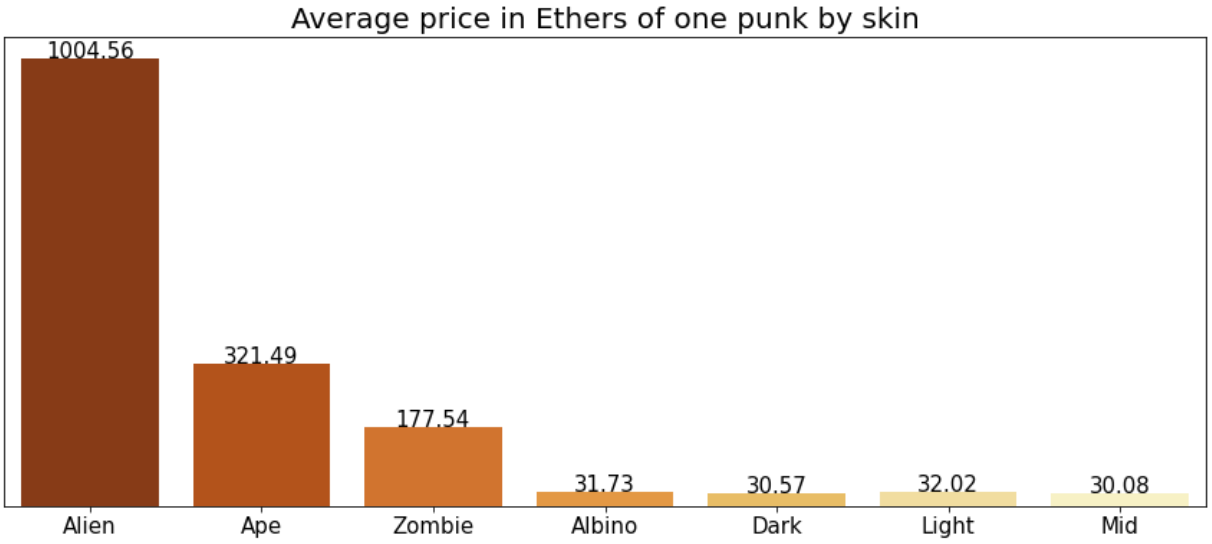

Figure 10. Average price by punk skin

4.1.6 Average price of one punk character by attribute

The actual price of each punk was considered as the average of the last sold amount. Punks with 1, 2, 3, 4 and 5 attributes have very similar average prices. On the other hand Groups of punks with 0, 6 and 7 attributes are very expensive.

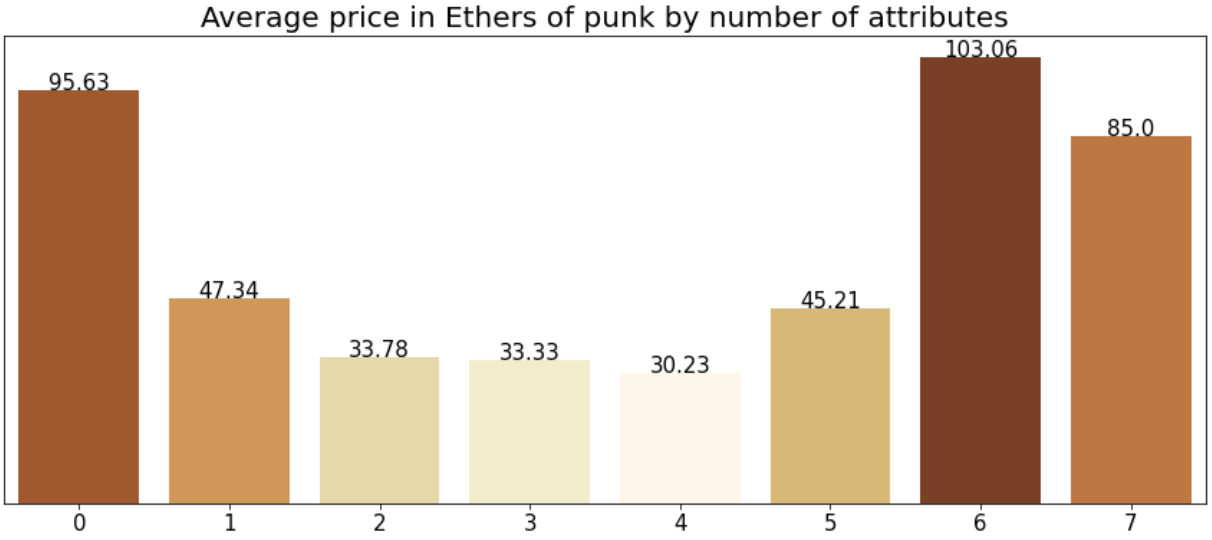

Figure 11. Average price of one punk by number of attributes

4.1.7 Punk characters available to buy by types

Available punks are considered as these which have some offered value by its owner. Punks from groups Female and Male are the most available to buy.

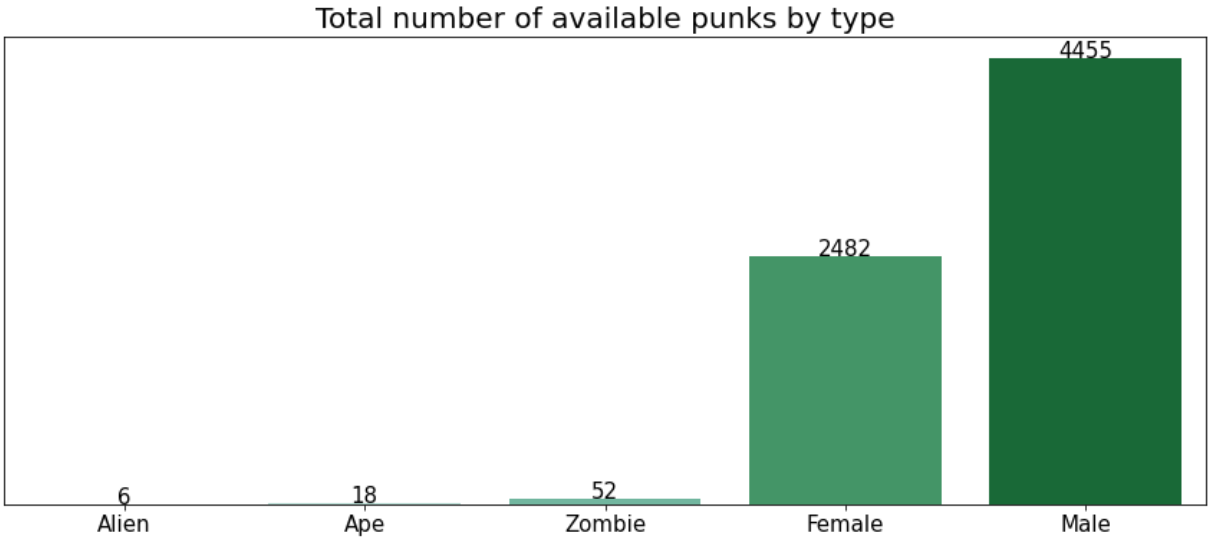

Figure 12. Available punks by type

4.1.8 Punk characters available to buy by skin

Available punks are considered as these which have some offered value by its owner. Punks from groups Dark, Light and Mid skin are the most available to buy.

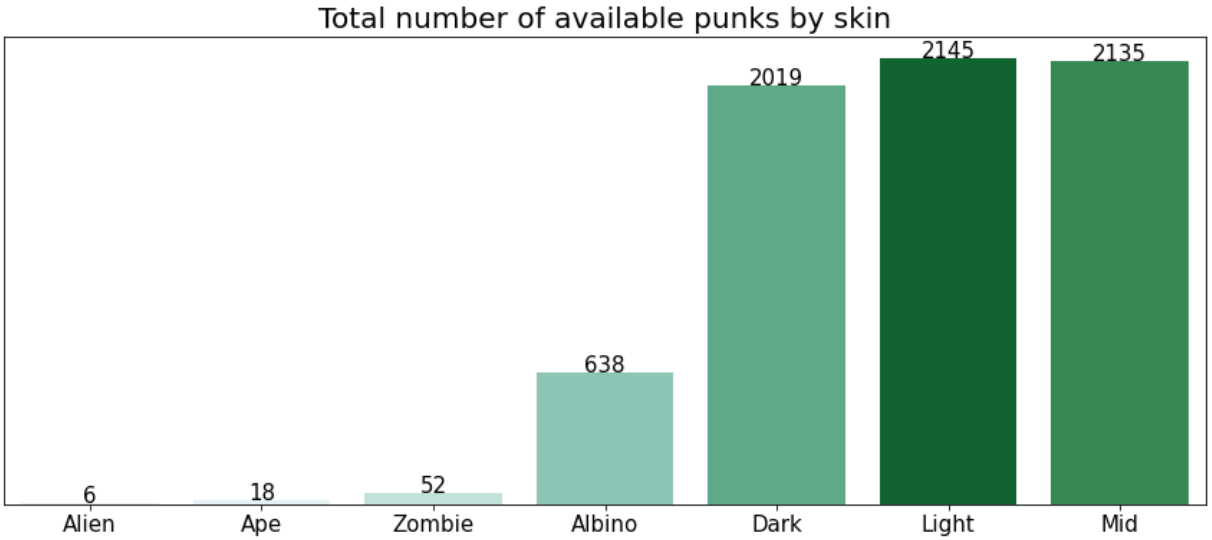

Figure 13. Available punks by skin

4.1.9 Punk characters available to buy by attribute

Available punks are considered as these which have some offered value by its owner. Punks with 3, 2 and 4 attributes are much more available than the others.

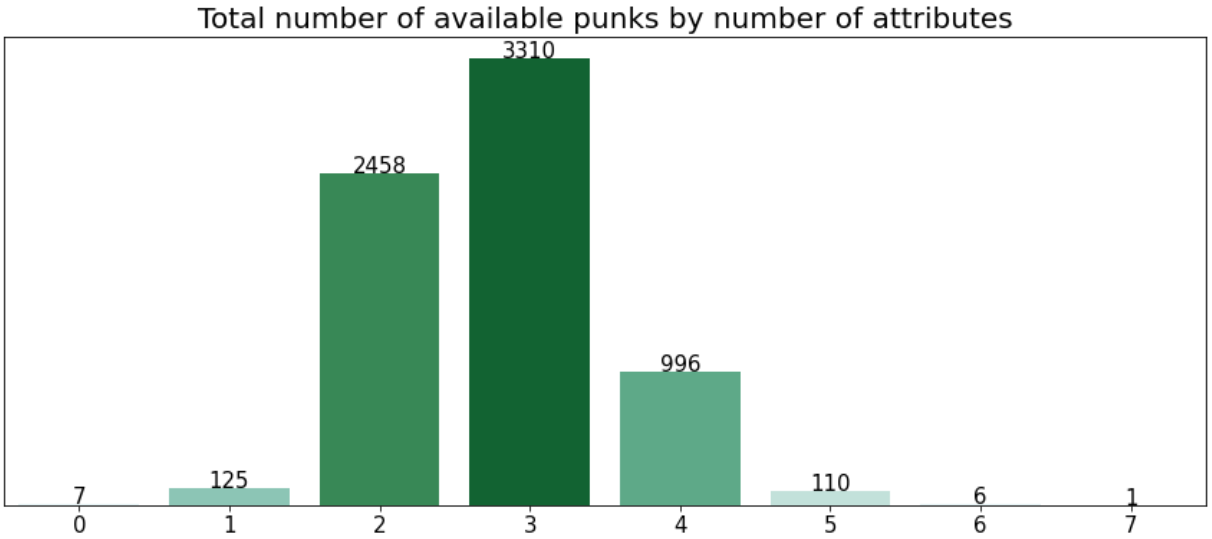

Figure 14. Available punks by number of attributes

4.1.10 Average rarest rank of punk character by type

The ranking of all characters was computed using the "harmonic mean" of the scarcity of their attributes. The best is the lowest number. The average ranking by each type varies very much between the best three groups of Aliens, Apes, Zombies and the groups of Females and Males. The Female characters have significantly better ranking than Male characters.

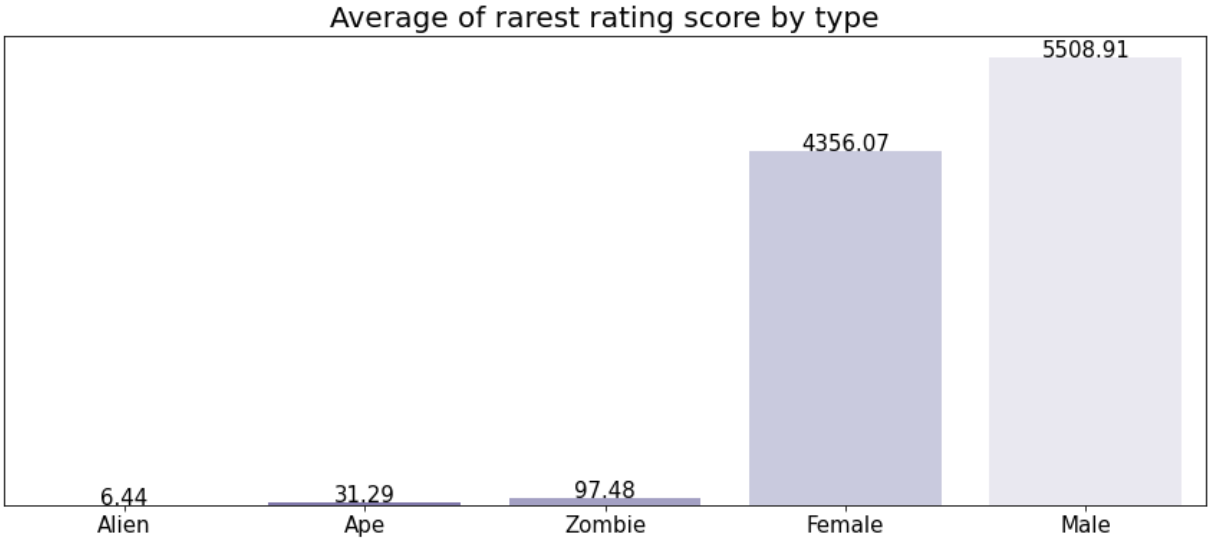

Figure 15. Average of rarest rating score by type

4.1.11 Average rarest rank of punk character by skin

The ranking of all characters was computed using the "harmonic mean" of the scarcity of their attributes. The best is the lowest number. Skin types Dark, Light and Mid have better ranking than Albino characters.

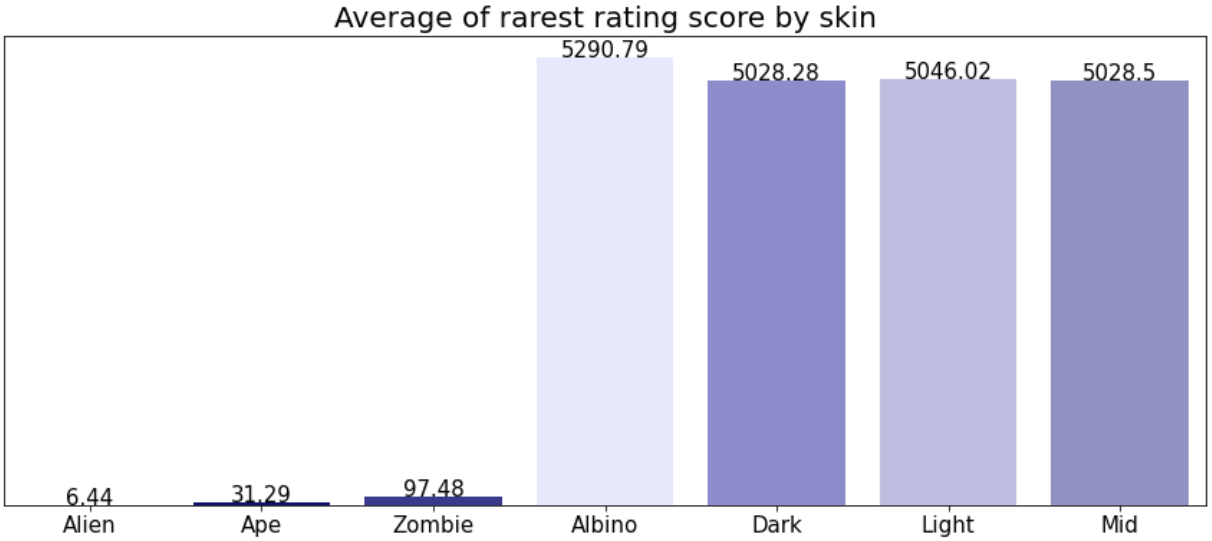

Figure 16. Average of rarest rating score by skin

4.1.12 Average rarest rank of punk character by attribute

The ranking of all characters was computed using the "harmonic mean" of the scarcity of their attributes. The best is the lowest number. Characters with none, six and seven attributes have much better rarest rating than the other characters.

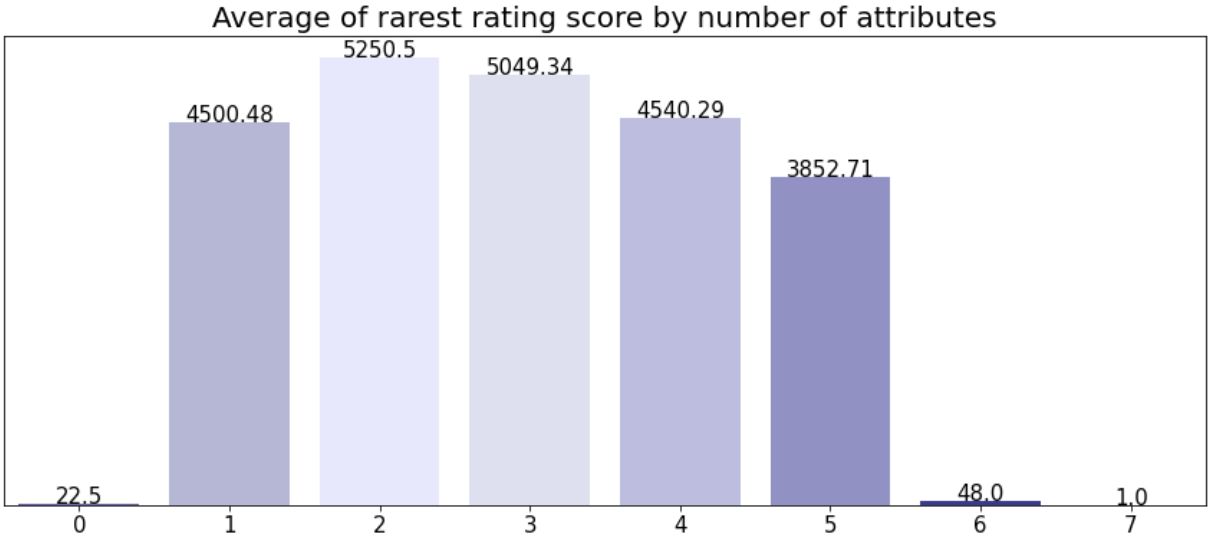

Figure 17. Average of rarest rating score by number of attributes

4.1.13 Conclusions

A relationship is observed **between rarest rank and price**. Characters like **Alien, Ape and Zombie have** low rarity ratings and are more expensive than others. Also these groups represent a small minority which could significantly influence the final results.

Most of the characters have two, three or four attributes. Characters with extreme values like none attribute or six or seven attributes have higher average price and there are few of them available for purchase.

Female characters **have better rarity ratings**, however **they are cheaper than male** characters.

4.2. General insights - transactions

4.2.1 Distribution of number of transactions

The distribution of the amount in Ethers of all sold and all bid transactions is showing that the amount is normally below 500 Ethers. The majority of market transactions are distributed between 0 to 200 Ethers. The highest sold and bid amount is 4200, the highest offered amount is 90 trillion of Ethers.

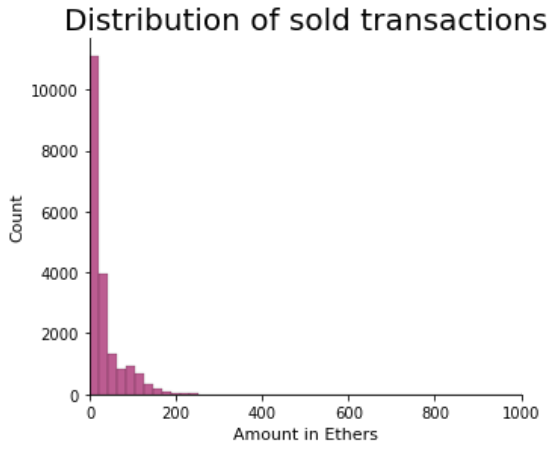

Figure 18. Distribution of sold transactions

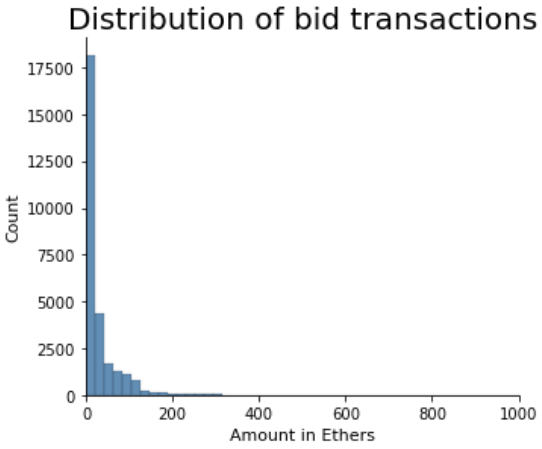

Figure 19. Distribution of bid transactions

4.2.2 Evolution of types of transactions during time

The evolution of the transactions is showing much more transactions from the beginning of 2021. It can be explained by increasing popularity of the art collection and also by these events:

11 March, 2021 - Beeple sold an NFT for $69 million at a first-of-its-kind auction at Christie's. The project called "Everydays," is a collage of Beeple's work created over 13 years. The project is revolutionary because it was the first time an NFT was sold for such a high price. [9]
24 June, 2021 - Exhibition of 5 CRyptoPunks in London offered at auction at Sotheby's brought by Swiss curator and digital art expert, Georg Bak. [10]

28 June, 2021 - Jay-Z puts a CryptoPunk NFT as his Twitter profile picture bought in the Sotheby's auction. [11]
7 August, 2021 - Axie Infinity hits 1 million daily active players, first NFT project to hit $1B all-time trade volume. This breakthrough gave much more visibility to all NFT's. [12]
14 December, 2021 - Punk 4156 bought for 2500 ETH (10 261 925.05 USD). [13]

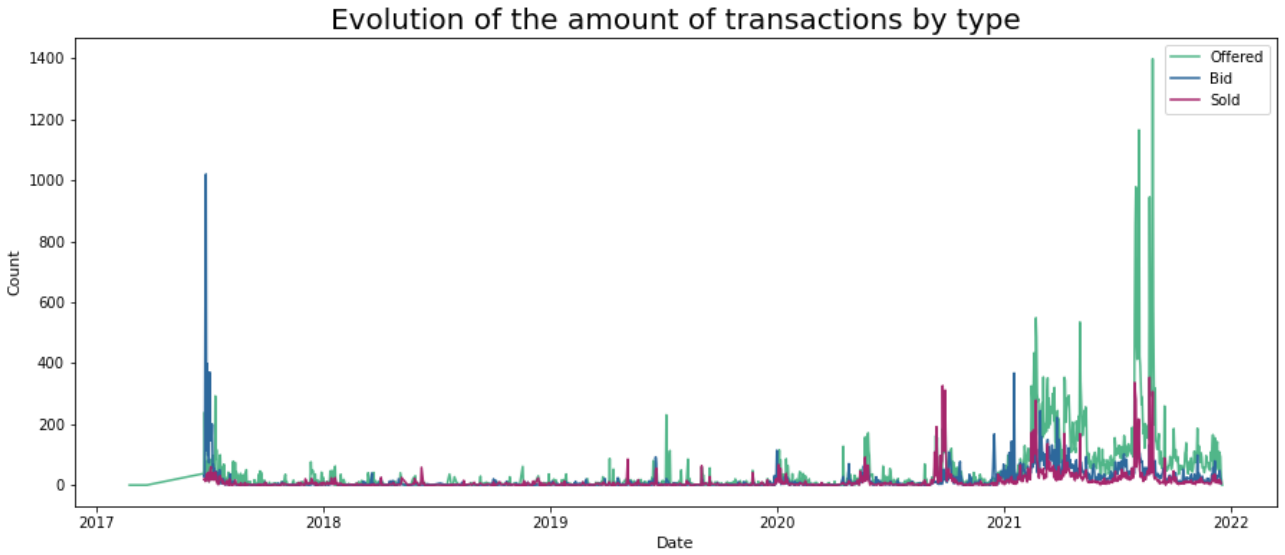

Figure 20. Evolution of the amount of transactions.

4.2.3 Evolution of sold transactions

The evolution of the sold transactions with its maximum and minimum has some very high peaks and has experienced an increase in the second half of the year 2021.

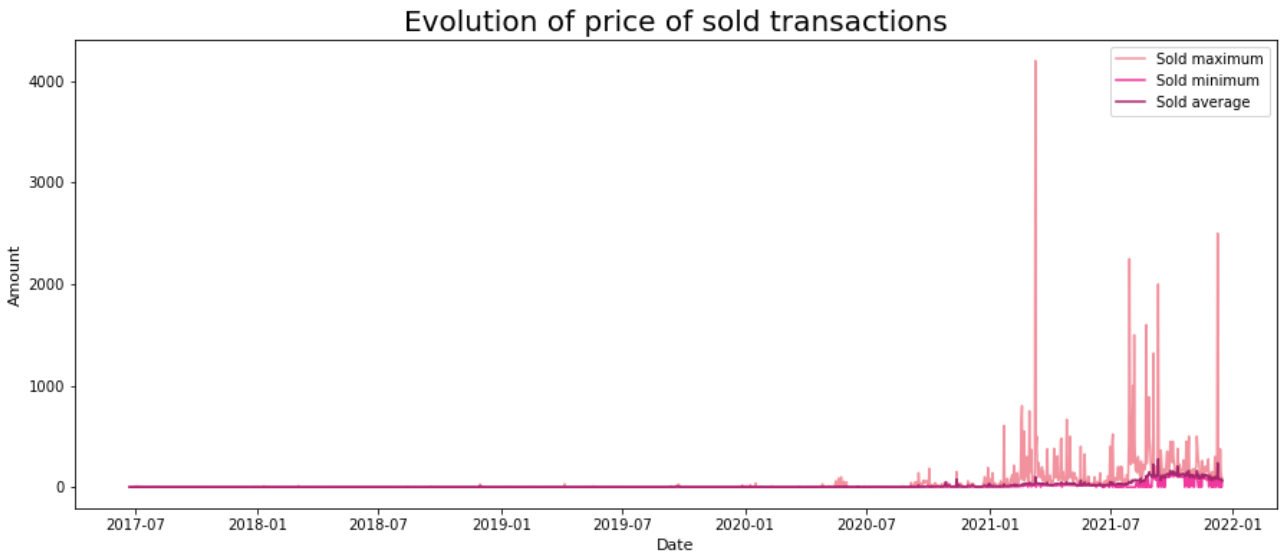

Figure 21. Evolution of the price of sold transactions.

4.2.4 Distribution of transactions

The distribution of the transactions shows that prices higher than 275 Ethers are very rare (95% quantile in Fig.23). Most of the sold transactions are lower value than 120 Ethers (466 235.06 USD).

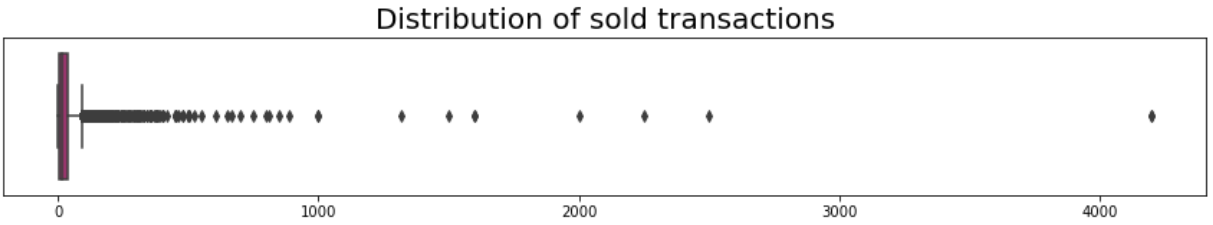

Figure 22. Distribution of the amount in sold transactions

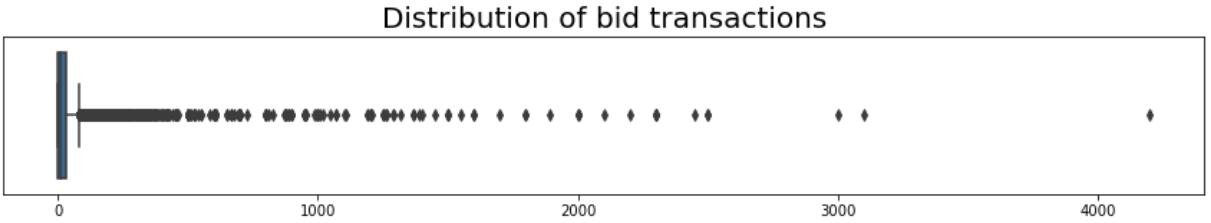

Figure 23. Distribution of the amount in bid transactions

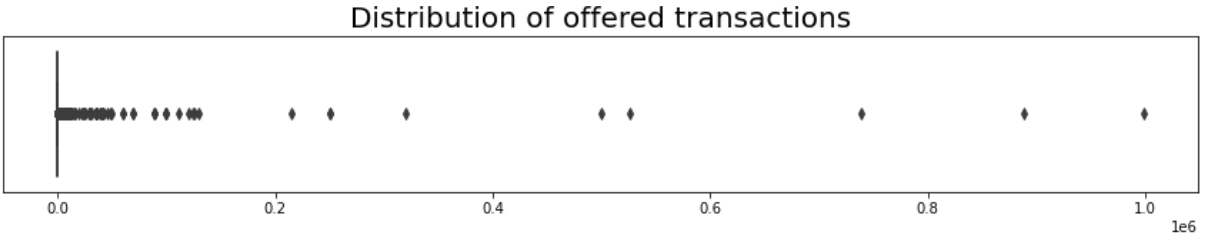

Figure 24. Distribution of the amount in offered transactions

Comparison statistics	**Last Sold transaction in Ξ**	**All Sold transactions in Ξ**	**All Bid transactions in Ξ**	**All Offered transactions in Ξ**
Median	2.25	16.98	10.00	35.00
Mean	18.55	32.21	31.8	194.81
STD	40.76	72.59	95.23	6837.92
25 % Quantile	0.30	1.70	0.33	12.75
75 % Quantile	22.99	38.00	32.5	99.0
95 % Quantile	88.57	120.00	112.00	275.0
Maximum	1320	4200	4200	999120.0

Figure 25. Statistical values of transactions in Ethers

The distribution of the offered transactions has some outliers which would distort the statistics of the whole group. Some offers were made with amounts containing symbols Y, Z, E, T, B, M and K. Amounts containing K have been understood as thousands, containing M as millions and other values containing Y, Z, E, T, B were eliminated (no clear explanation of their meaning).

4.2.5 Proportion of sold transactions by type

The proportion of all transactions made suggests that Male characters are much more frequent in transactions than other types.

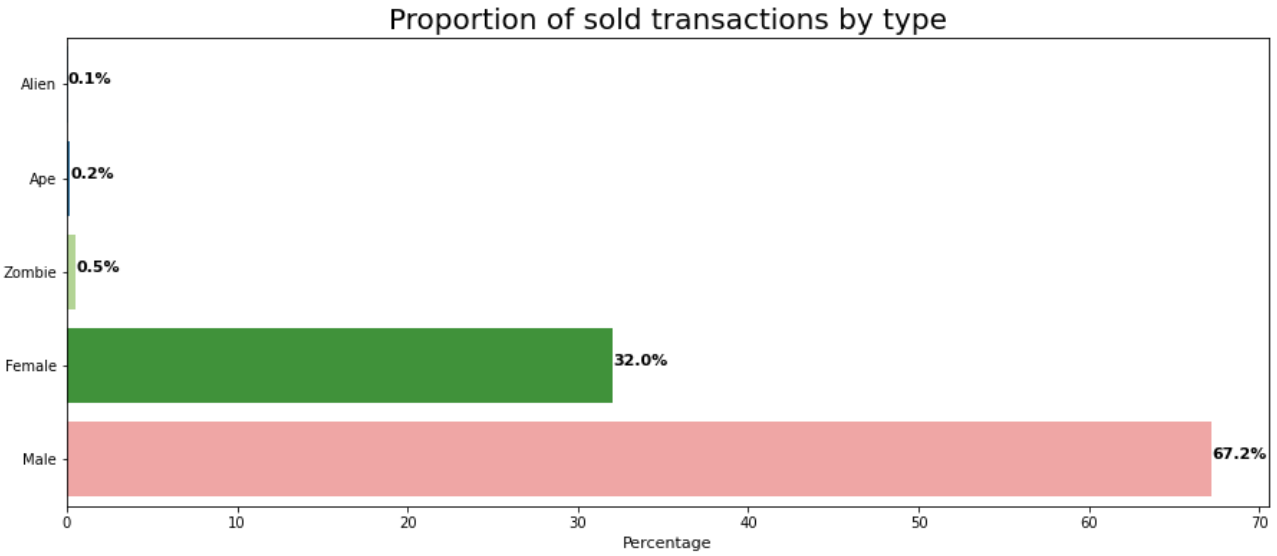

Figure 26. *Proportion of sold transactions by type*

4.2.6 Proportion of sold transactions by skin

The proportion of all transactions grouped by skin type shows that most of the transactions are involving dark skin characters.

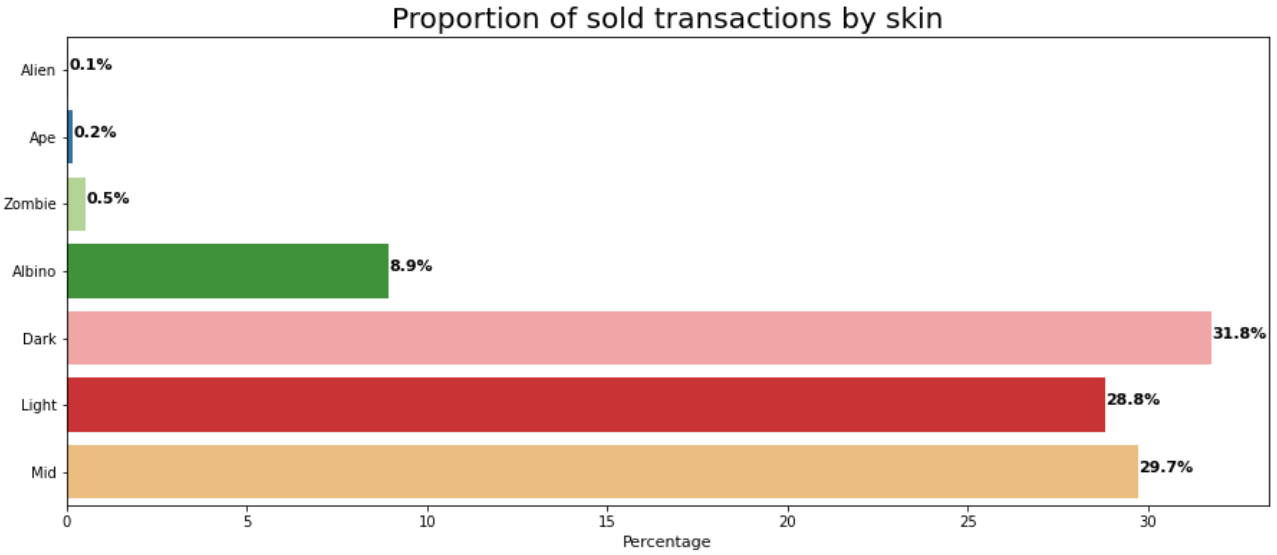

Figure 27. *Proportion of sold transactions by skin*

4.2.7 Proportion of sold transactions by attributes

The proportion of all transactions grouped by number of attributes shows that most of the transactions involve characters with 3 attributes.

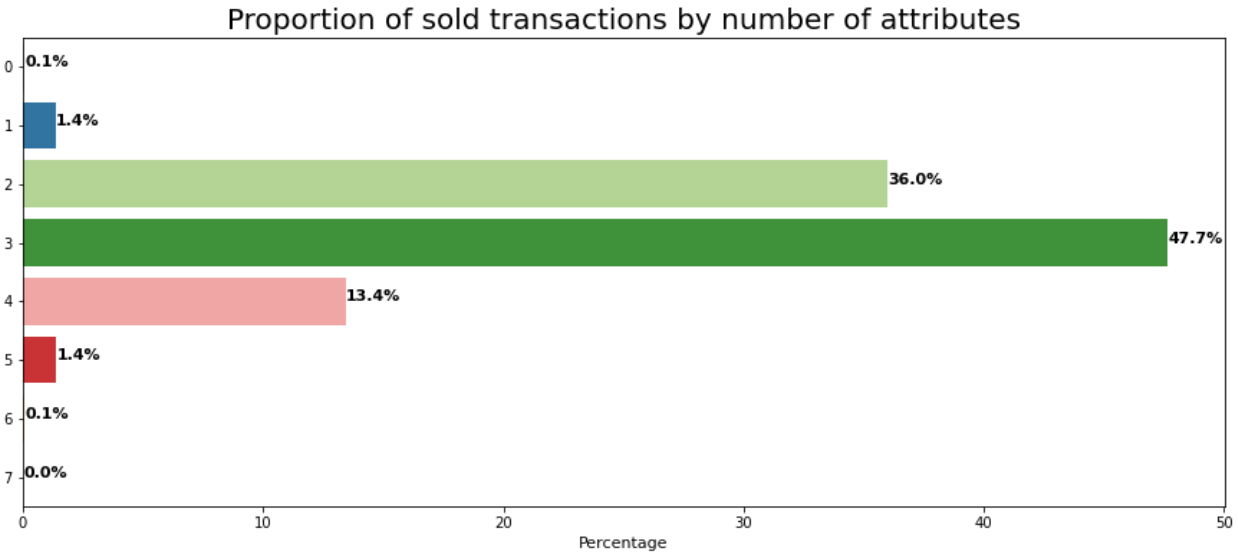

Figure 28. *Proportion of sold transactions by attributes*

4.2.8 Evolution of sold transactions by type

The evolution of the sold price by each type shows that Aliens, Apes and Zombies are getting much more valuable than the other groups. Female and Male characters are presenting more stable prices.

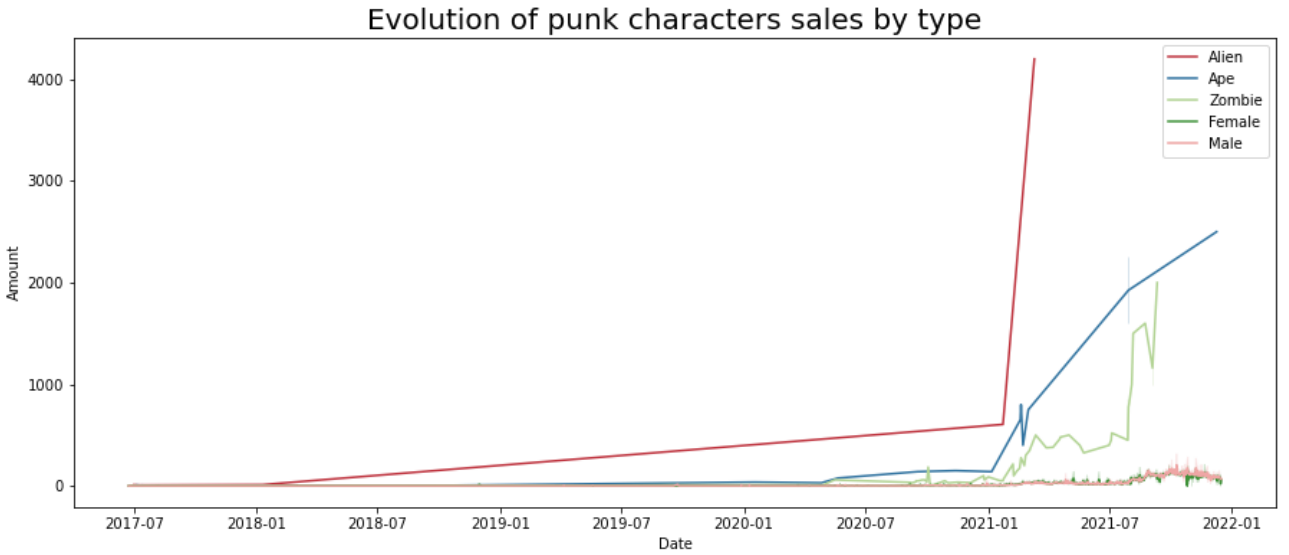

Figure 29. *Evolution of sold transactions by types*

4.2.9 Evolution of the amount of sold transactions and prices

The evolution of all transactions and sold prices is a good measure of the market evaluation. Starting 2021 we can observe that the number of transactions increased and so did the total amount of Sold prices. There is a correlation between these two features, so the number of total transactions should be taken into account for analysis on day-to-day evolution of the price of a specific character.

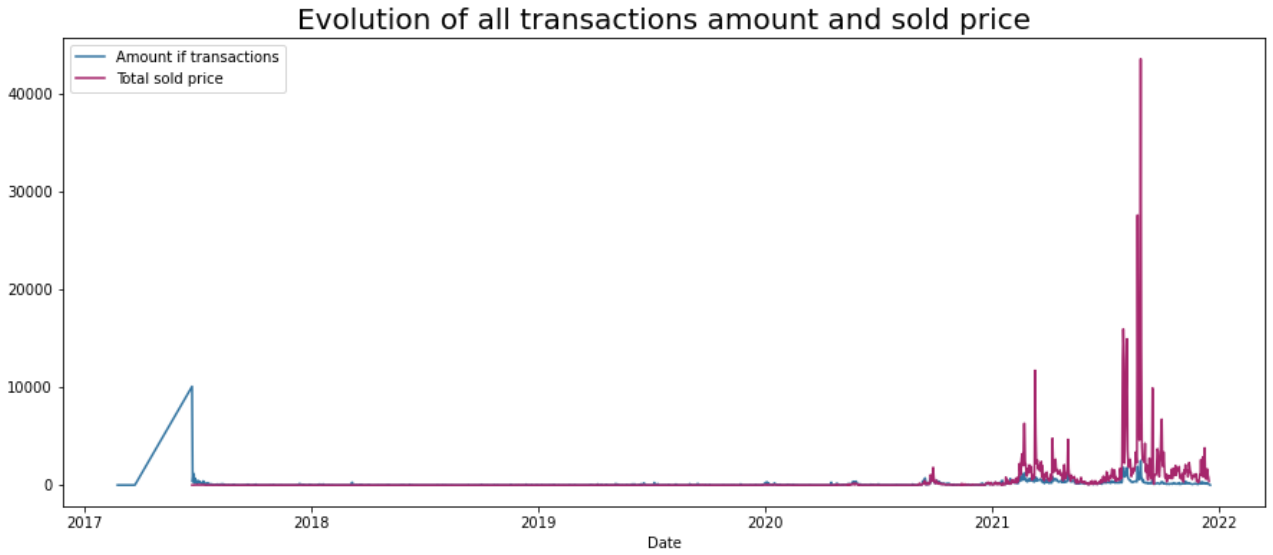

Figure 30. *Volume of transactions and price amount*

4.2.10 Conclusions

The evolution of transactions reveals a **relatively stable sales market in the Female and Male group** since the beginning of 2021.

There are **some extreme peaks** with random occurances in price values. Most of the prices of sold transactions stay below 120 ETH which is approximately 459000 in american dollars.

Some action by **celebrities or auction companies has an impact on the price** market evolution and increases the amount of transactions as well.

Evolution of the **price of Alien, Ape and Zombie type would be very difficult to predict** because of the high instability and strong peaks in the price history.

5. Predictive analysis

5.1. Consideration

Prices used in predictive analytics are **expressed in Ethers** because it is the one of NFT ecosystem currency used for transactions. [14]

The price of each character is considered as the **transactions of type "Sold"**. The rest of transactions like "Bid" or "Offered" were not taken into account because these amounts can be a result of speculation and market unpredictability.

Some outliers were removed from the final database, such as characters with transactions of more than 120 ETH. This value was taken by observing the 95% quantile of all sales transactions distribution.

Groups of Aliens, Apes and Zombies have not been included for the classification. These groups have very different market evolution, prices and are also very rare. That's why these types already form a separate group with their specific characteristics.

Additional feature is the profit calculated as a **difference between the last and second last sale**.

Final features for the classification analysis are: Punk number, Skin type, Type, Rarest rank, Total number of attributes, Last sold price, Number of sold transactions, Total amount in sold transactions, Total number of all transactions, Highest price, Last sold price difference, Current hold time. The features were selected while studying analytics metrics of the NFTGO website. [15]

For better evaluation the art collection would be good to consider also the popularity index, evolution of cryptocurrencies and collection value index. These features were not included in the further study.

The aim of the classification is to divide CryptoPunks characters in groups and observe the characteristics within each cluster in order to determine **which cluster would be interesting for investment.**

5.2. Classification

5.2.1 Preparation

All features were scaled with **standard scaler method** to prevent the result from being influenced by the measurements. Also, the feature of the punk id number was removed because it is the only non-quantitative feature.

PCA analysis was used for reducing the dimensionality of features and creating new features which have most of the variance of the original data. Also this process reduces the computational cost and improves model performance.

To identify the optimum number of clusters **KneeLocator method** was used because the Elbow method results look ambiguous (Fig. 31).

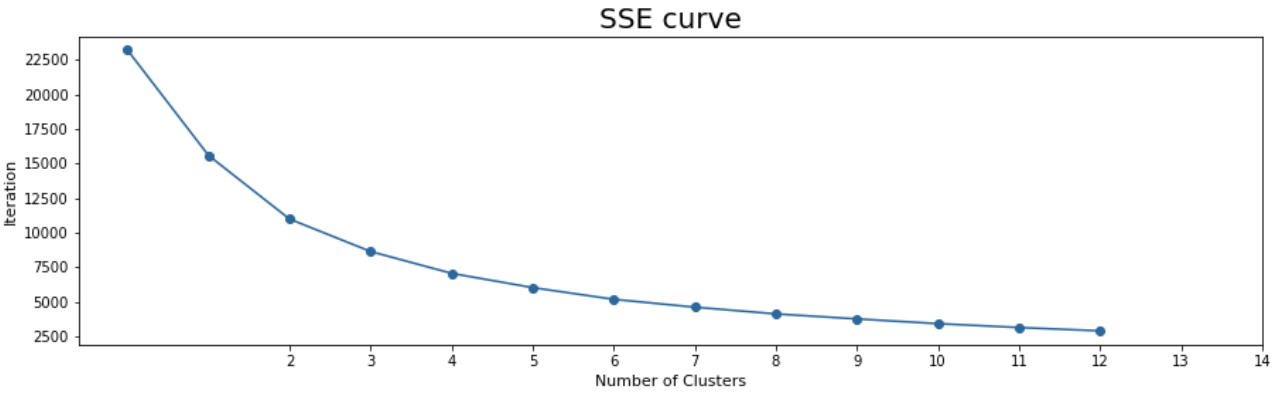

Figure 31. *Elbow method to find the best number of clusters*

The optimum number of clusters from KneeLocator is 4. **Silhouette curve** (Fig. 32) is another way of interpretation and validation of consistency within clusters of data and shows a possible number of **4 or 8 clusters**. Unsupervised Machine Learning algorithm was used to identify patterns difficult to see by simple observation and descriptive analysis testing models with 4 and 8 clusters. Results were compared by silhouette score.

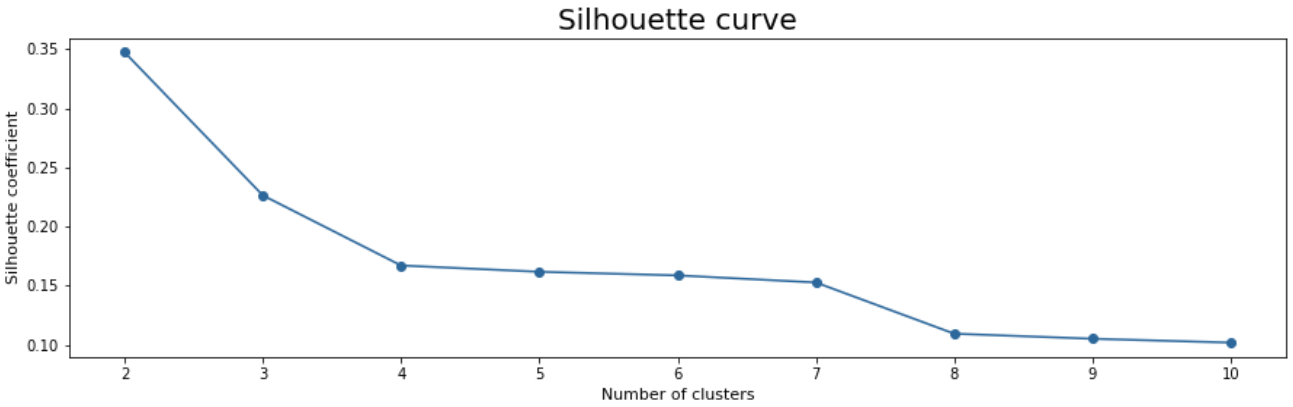

Figure 32. *Silhouette curve*

5.2.2 Results - 4 clusters

Silhouette score with 4 clusters is 0.51.

Figure 33. *Cluster representation - 4 clusters.*

5.2.2 Results - 8 clusters

Silhouette score with 8 clusters is 0.60. This score means that a model with 8 clusters is more accurate and the entities are less overlapped than the previous case.

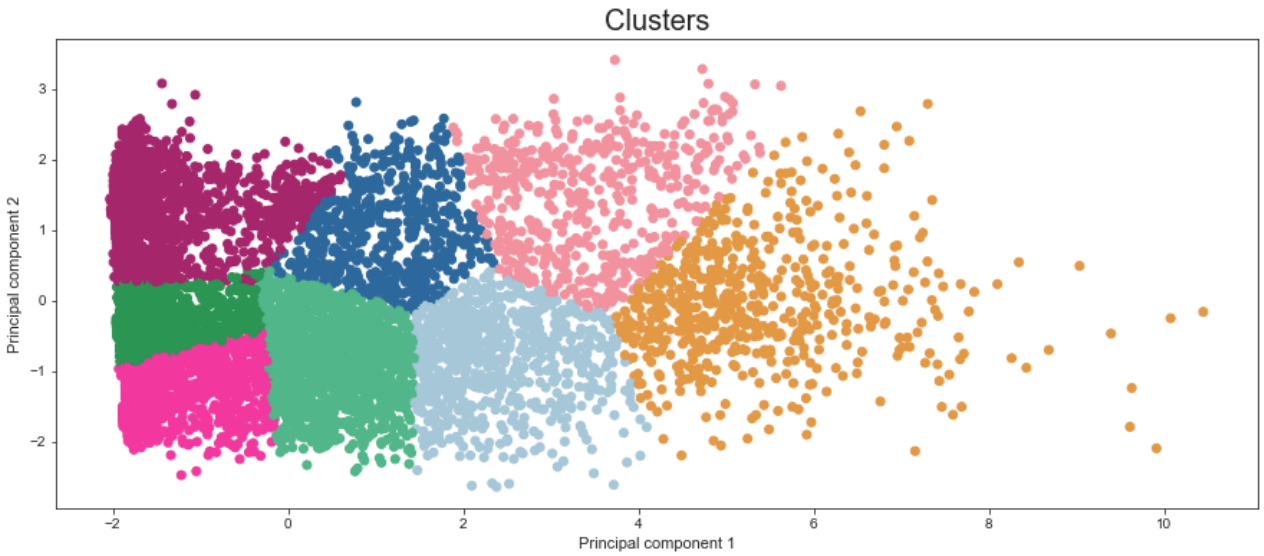

Figure 34. *Cluster representation - 8 clusters.*

From the number of characters (fig.35) in each cluster it's obvious that the clusters are not divided by types, skins or number of attributes. The total number of characters in each cluster is quite proportionally distributed, but this fact is contradictory to the distribution analysed in previous steps. For example there are very few characters of type Alien, and very few with no attributes.

Cluster	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**	**Cluster 8**
Total	1384	584	592	518	1229	2105	1949	745

Figure 35. *Number of characters in the final clusters.*

Cluster 3 has the highest average difference between last two sold prices and also the **highest average amount of sold price** (fig.36). The average number of sold transactions is 5.87 which is more than the other clusters. The total number of transactions is high, that might point to higher liquidity of these characters because of higher frequency of sales. This cluster might be interesting for further study and possible investment.

Average by cluster	**Difference in last two prices**	**Last sold price**	**Number of sold transactions**	**Total number of transactions**	**Highest sold price**
Cluster 1	3.248663	18.709863	2.764451	19.405347	20.301257
Cluster 2	7.515360	33.785805	2.604452	24.453767	34.938630
Cluster 3	40.231470	93.781334	5.869932	45.550676	96.020473
Cluster 4	26.309112	77.958494	3.202703	31.513514	79.340792
Cluster 5	0.003751	1.031774	0.746949	7.235964	1.220130

Cluster 6	0.044342	1.984822	0.441805	7.942043	2.113644
Cluster 7	0.048574	0.355762	0.347871	5.895331	0.359887
Cluster 8	12.595235	44.966832	4.755705	33.099329	46.739195

Figure 36. *Clusters statistics average*

Observing the number of characters by skin in cluster 3, the majority is **Female dark skin and Male dark skin** (fig.37). The feature of Dark skin would be important for selecting the best characters for investment.

The cluster 3 contains characters with 1, 2, 3, 4 and 5 total attributes. From the previous exploratory analysis we know that characters with a more extreme number of attributes are likely to be more expensive. That's why for the future investment **characters with 1 and 5 attributes** would be better for investment (fig.38).

There are 3259 characters with the **last two sold price differences higher than 0** (fig.39). In cluster **3 there are 528 characters** (fig.40) with this good result out of 592 total characters in this cluster.

Type	**Female Albino**	**Female Dark**	**Female Light**	**Female Mid**	**Male Albino**	**Male Dark**	**Male Light**	**Male Mid**
Cluster 1	26	85	70	64	105	320	360	354
Cluster 2	32	129	123	137	6	28	53	76
Cluster 3	17	49	32	39	51	167	115	122
Cluster 4	27	90	123	138	7	33	49	51
Cluster 5	7	17	15	6	166	343	365	310
Cluster 6	184	497	508	544	18	98	107	149
Cluster 7	80	138	173	155	129	380	440	454
Cluster 8	18	28	20	19	57	220	195	188

Figure 37. *Clusters statistics by type and skin*

Attribute	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Cluster 1	1	15	520	661	180	7	0	0
Cluster 2	1	4	172	270	124	11	2	0
Cluster 3	0	5	233	269	76	9	0	0

Cluster 4	0	4	123	258	108	23	1	1
Cluster 5	0	86	639	448	54	2	0	0
Cluster 6	3	69	622	907	427	71	6	0
Cluster 7	1	93	617	949	272	17	0	0
Cluster 8	0	14	292	362	76	1	0	0

Figure 39. *Clusters statistics by attribute*

Difference in last two sold prices	**Number**
Lowest in Ethers	-114.8
Average in Ethers	6.14
Lower than 0 - number of characters	442
Equal to 0 - number of characters	5405
Higher to 0 - number of characters	3259

Figure 40. *Clusters statistics of last sold prices*

Difference in last two sold prices	**Higher than 0**	**Total characters in cluster**
Cluster 1	859	1384
Cluster 2	599	584
Cluster 3	528	592
Cluster 4	409	518
Cluster 5	399	1229
Cluster 6	196	2105
Cluster 7	162	1949
Cluster 8	107	745

Figure 41. *Number of characters in each cluster with positive last sold prices difference*

Cluster 5, 6 and 7 contain a lot of characters with differences between the **last two sold prices close to 0**. That might mean that these characters have never been sold yet (fig.41).

Cluster 1 has some high negative values in differences between the last two sold prices (fig.41). This cluster **would not be good for investment**.

Cluster 3 has almost all values of **differences between the last two sold prices higher than 0** (fig.41) and the distribution is quite proportional.

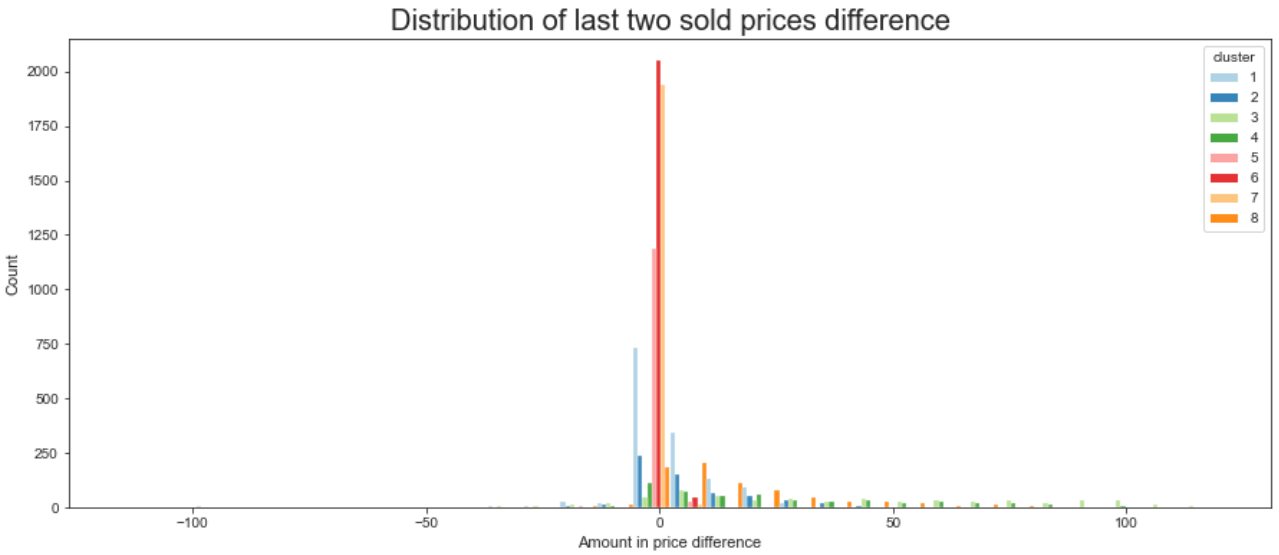

Figure 42. *Distribution of values of price difference between last two sold transactions.*

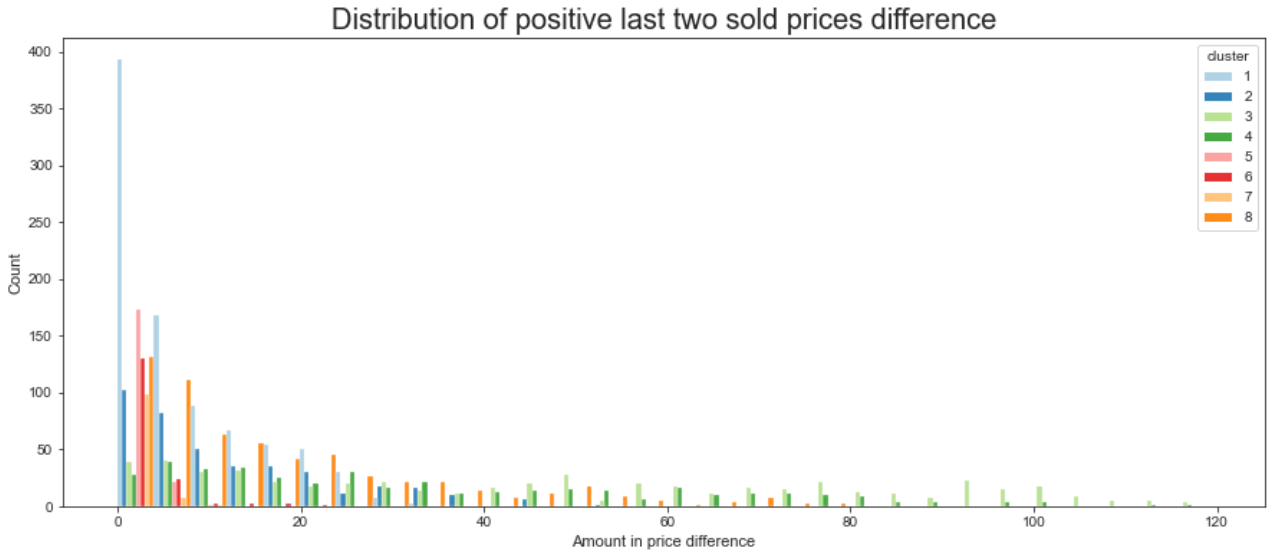

Figure 43. *Distribution of positive values of price difference between last two sold transactions.*

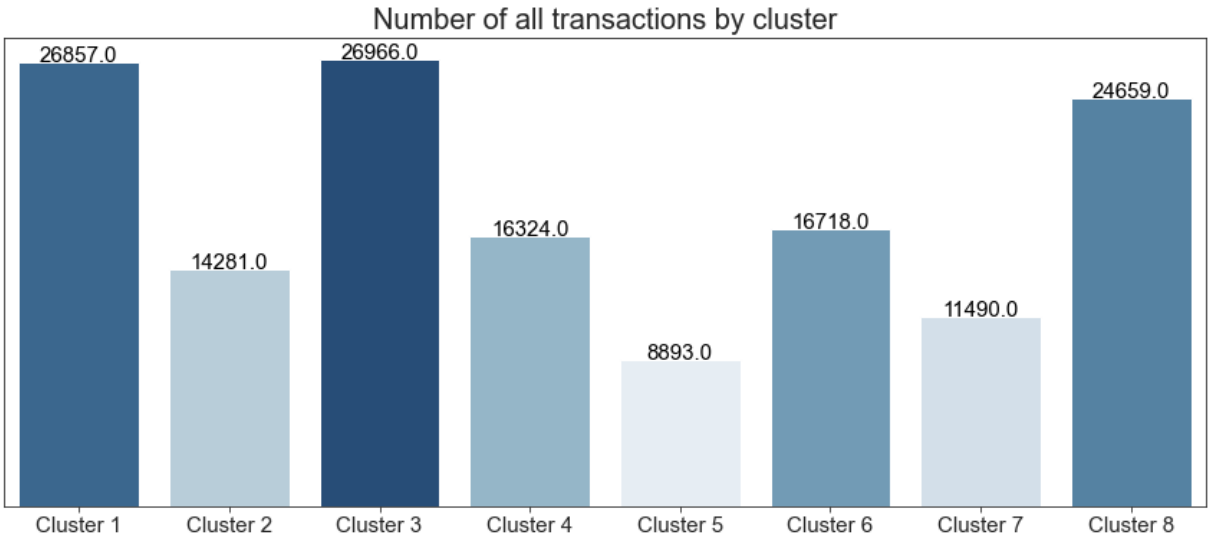

Figure 44. *Distribution of total transactions by cluster*

Cluster 1 and cluster 8 have a very high number of all transactions and also a high number of sold transactions. Characters in these groups are more likely to be sold, bid or offered than the other clusters (fig.44).

Cluster 3 has the highest number of all transactions and also a very high number of sold transactions (fig.45).

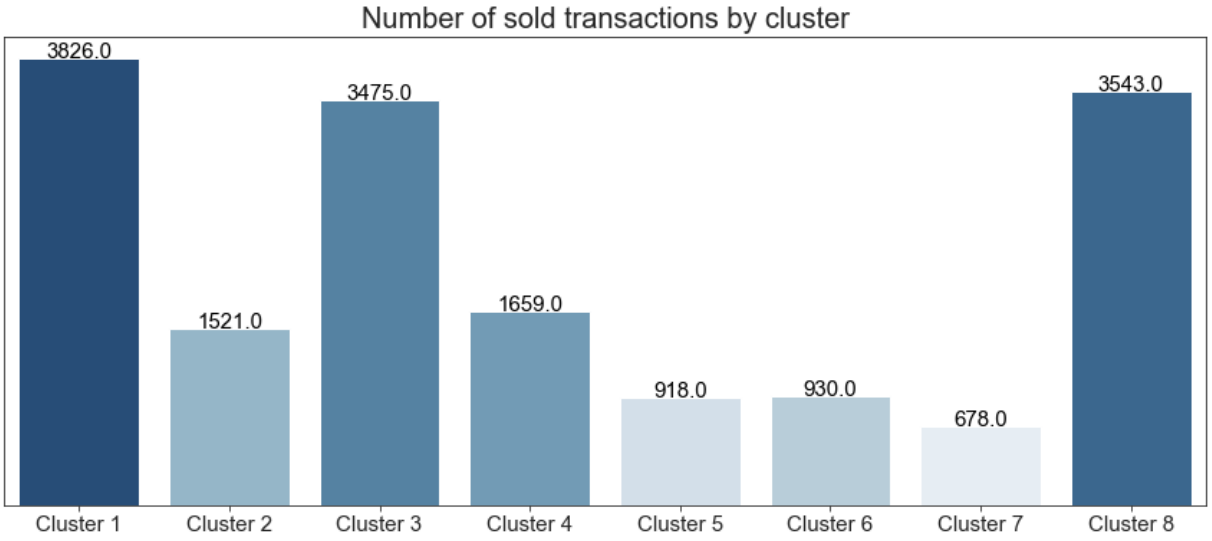

Figure 45. *Distribution of total sold transactions by cluster*

5.2.3 Clusters comparison

Cluster 1 - Mostly Male characters. High number of characters which have a difference between the last two sold prices below or equivalent 0. Highest total amount of sold transactions. Average rating.

Cluster 2 - Mostly Female characters. High number of characters which have a difference between the last two sold prices below or equivalent 0. Poor rating.

Cluster 3 - Female and Male characters proportionally distributed. Almost all characters which have a difference between the last two sold prices higher than 0. Highest total amount of all transactions and high total amount of sold transactions. **Best rating in all aspects.**

Cluster 4 - Female and Male characters. A lot of characters which have a difference between the last two sold prices higher than 0. Second best rating.

Cluster 5 - Mostly Male characters. A lot of characters which have a difference between the last two sold prices equal to 0. Very low number of total transactions. Poor rating.

Cluster 6 - Mostly Female characters. A lot of characters which have a difference between the last two sold prices equal to 0. Very low number of total transactions. Poor rating.

Cluster 7 - Female and Male characters proportionally distributed. A lot of characters which have a difference between the last two sold prices equal to 0. Very low number of total transactions. Average rating.

Cluster 8 - Female and Male characters, low number of Female characters. High number of characters which have a difference between the last two sold prices below or equivalent 0. Poor rating.

5.2.4 Conclusions

The NFT market is highly influenced by external events and for this reason we can talk of **high volatility**. Market experiences periods of unpredictable, and sometimes sharp, price movements.

There is a **great difference between groups** of Aliens, Apes, Zombies on the one side and Female and Male groups on the other side.

Groups of Aliens, Apes and Zombies represent high risk investment because of its unpredictable evolution on the market. Also these groups have the highest average prices and are very rare.

5.2.5 Final selected group of males

Three best characters selected by highest difference between last two sold prices.

The character with the highest difference between last two sold prices is Punk number 5023. The cheapest character from this group is Punk number 6007.

Albino skin Male	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	1241	2	109.00	35	103.00
	3317	2	105.00	53	101.50
	6363	2	103.03	38	86.17

Dark skin Male	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	5023	4	118.49	14	118.41
	4953	4	115.00	43	114.85
	2416	2	114.44	27	113.94

Light skin Male	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	2728	4	115.95	20	115.95
	8322	3	114.99	26	114.99
	4861	2	118.90	35	113.45

Mid skin Male	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	9005	2	116.0	102	108.00
	4482	3	104.0	6	103.87
	6007	3	102.0	22	100.65

5.2.6 Final selected group of females

Three best characters selected by highest difference between last two sold prices.

The character with the highest difference between last two sold prices is Punk number 6125. The cheapest character from this group is Punk number 3768.

Albino skin Female	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	6637	3	111.00	30	94.00
	6187	2	99.00	78	77.00
	3768	2	80.99	42	75.99

Dark skin Female	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	6125	4	118.50	46	118.50
	5074	4	115.00	13	105.50
	2915	4	115.00	15	105.11

Light skin Female	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	3675	3	100.00	24	99.82
	5628	4	118.69	11	98.99
	3420	2	95.00	43	95.00

Mid skin Female	Id number	Total attributes	Last sold price in Ξ	Number of all transactions	Difference in last two prices in Ξ
	7305	3	119.00	23	116.55
	5094	3	115.00	6	114.65
	8406	3	111.00	17	110.90

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