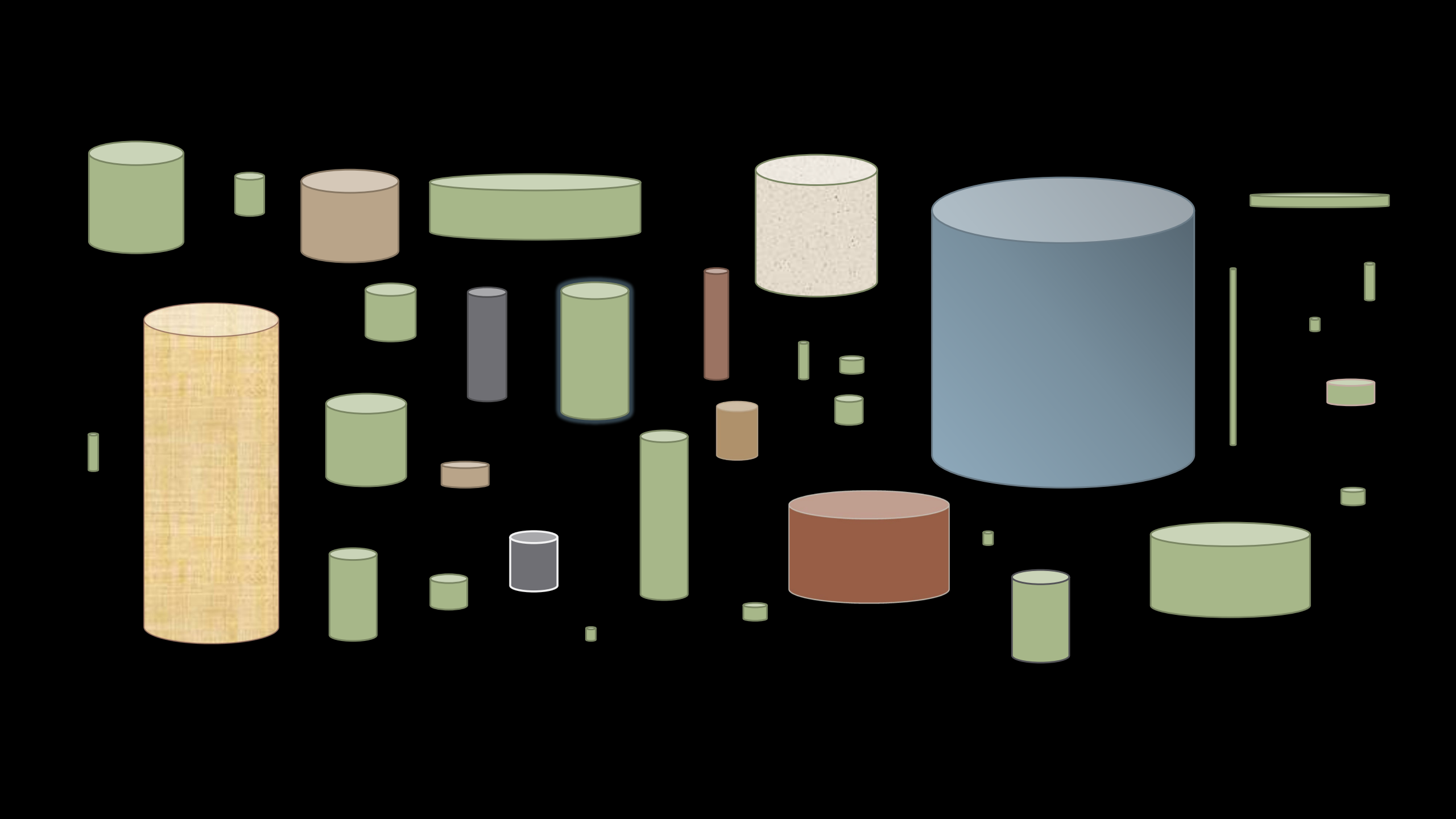
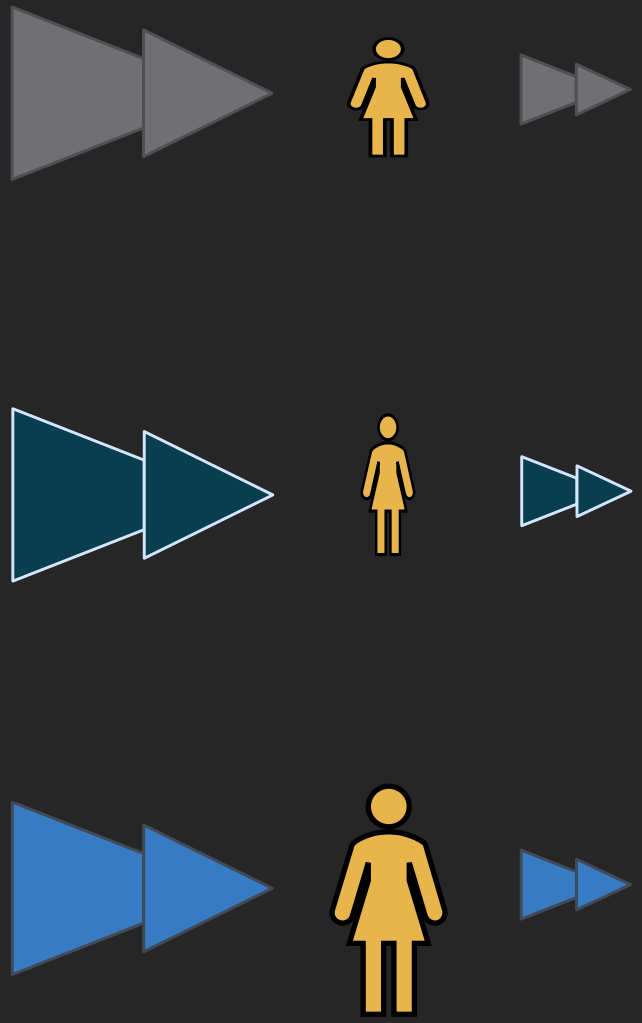
Metody i narzędzia *Big Data*

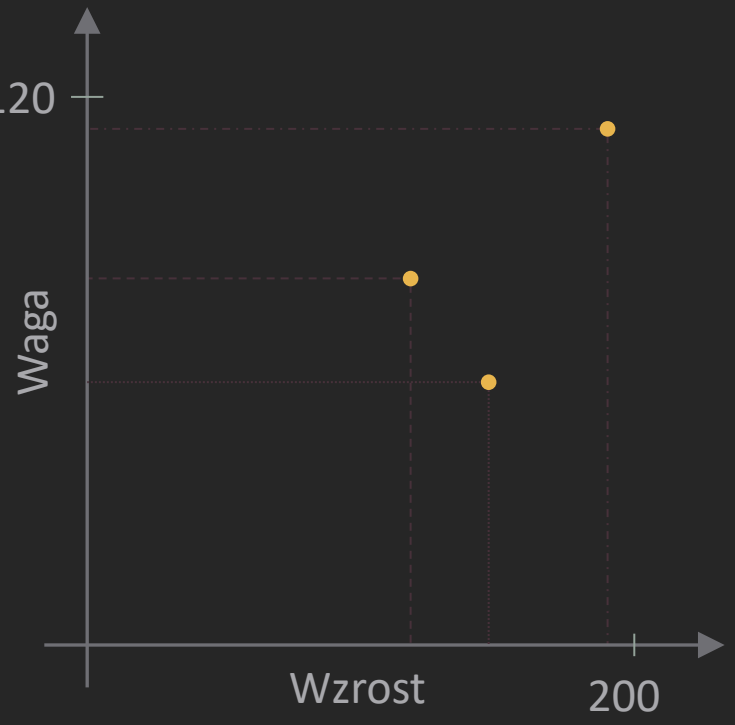
Przestrzeń osadzeń

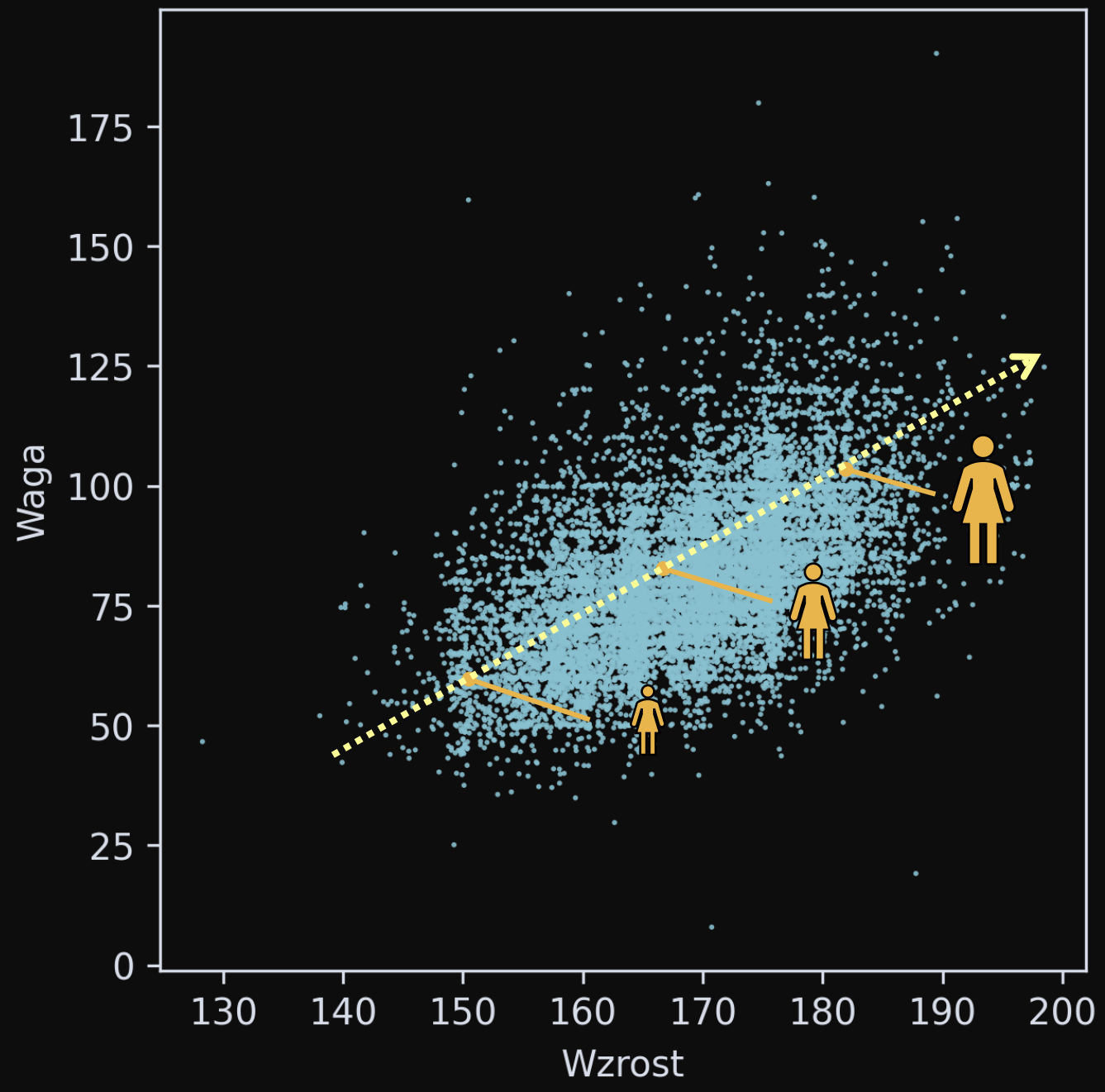


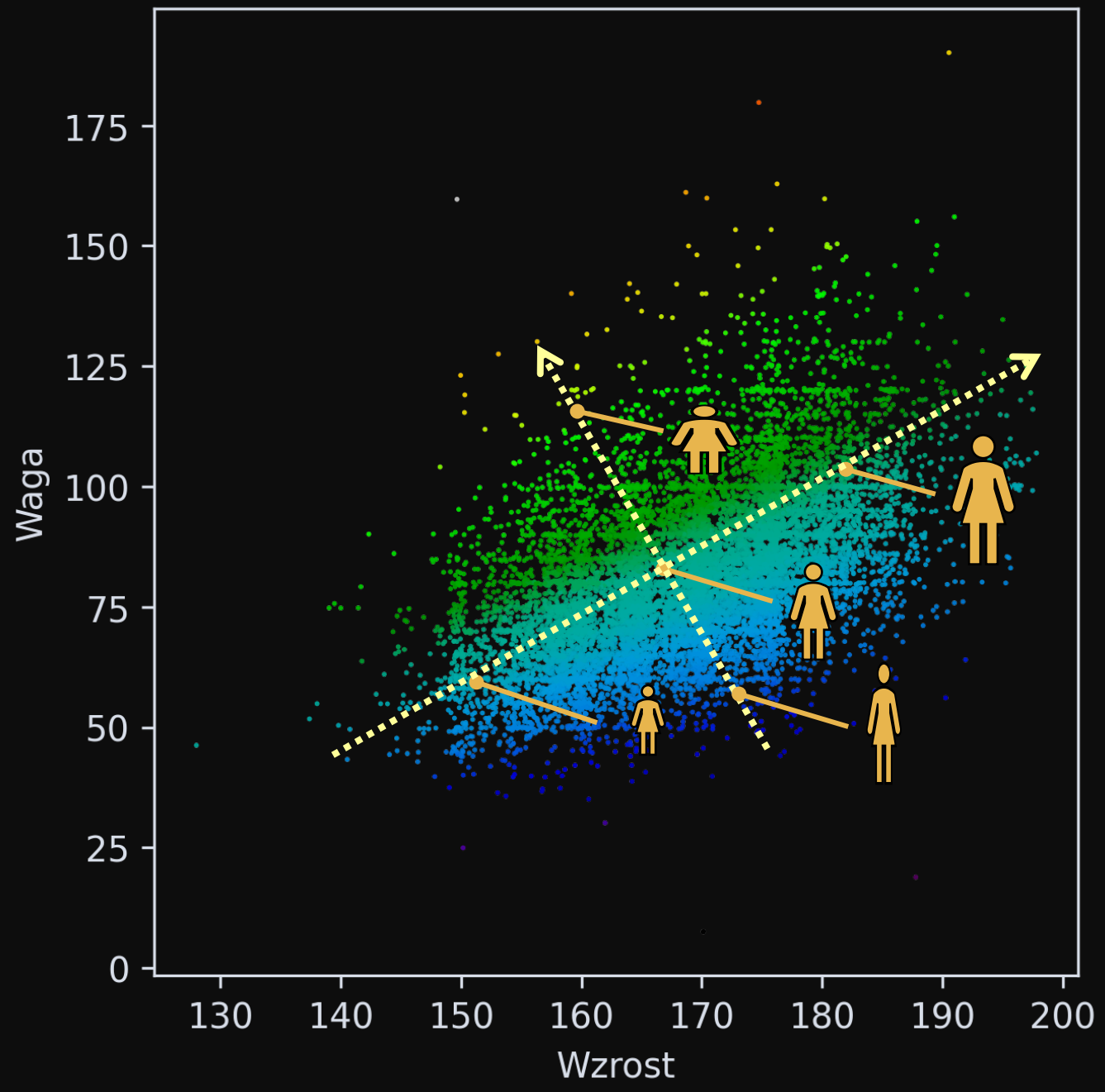

wysokość
średnica podstawy

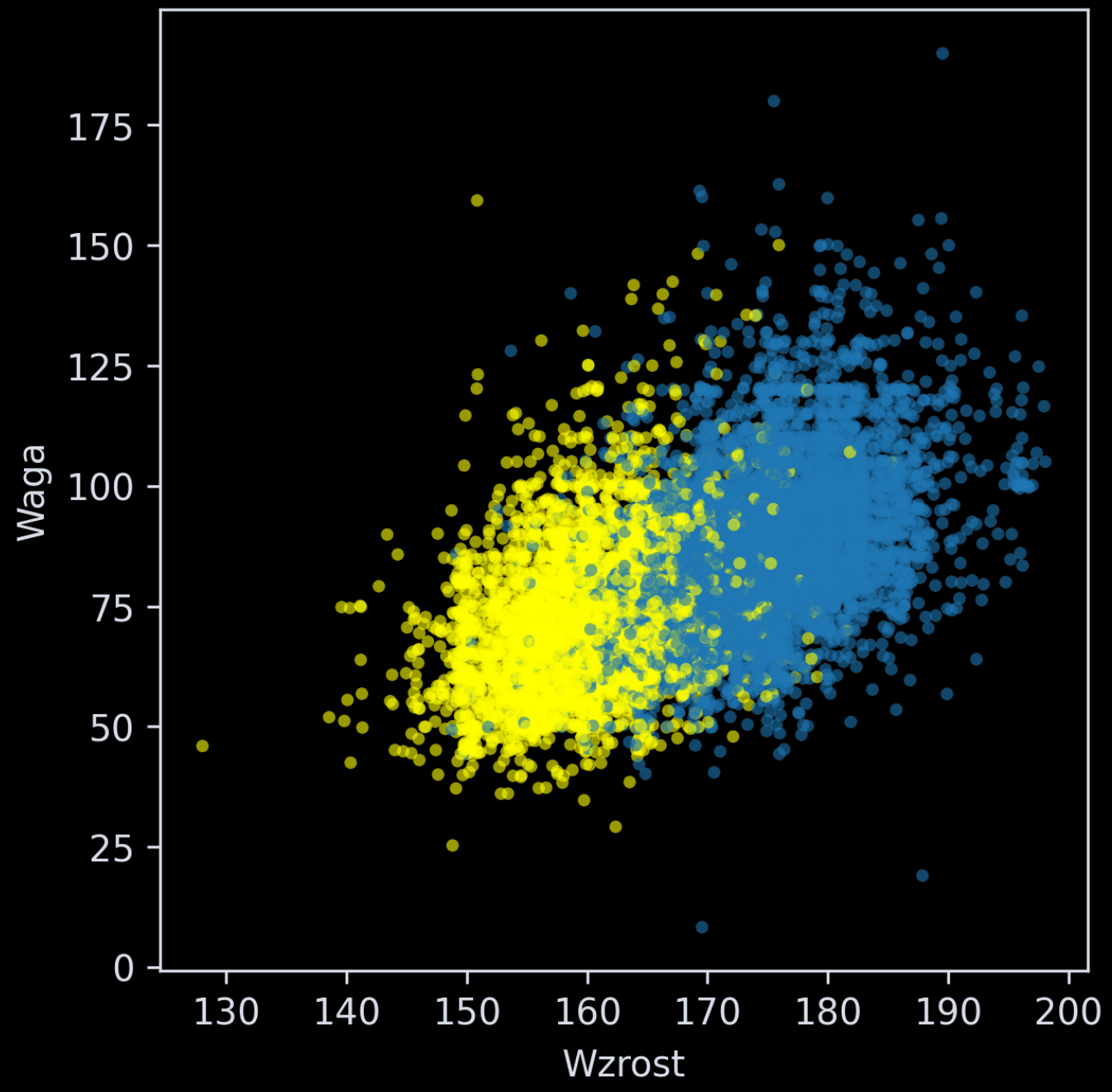

alamy
alamy
alamy

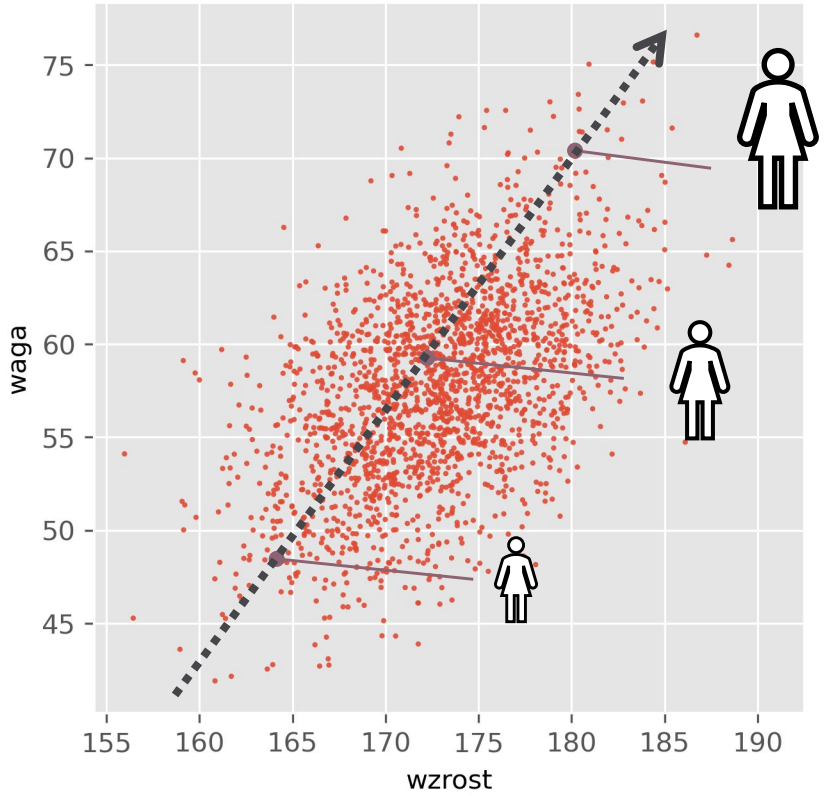


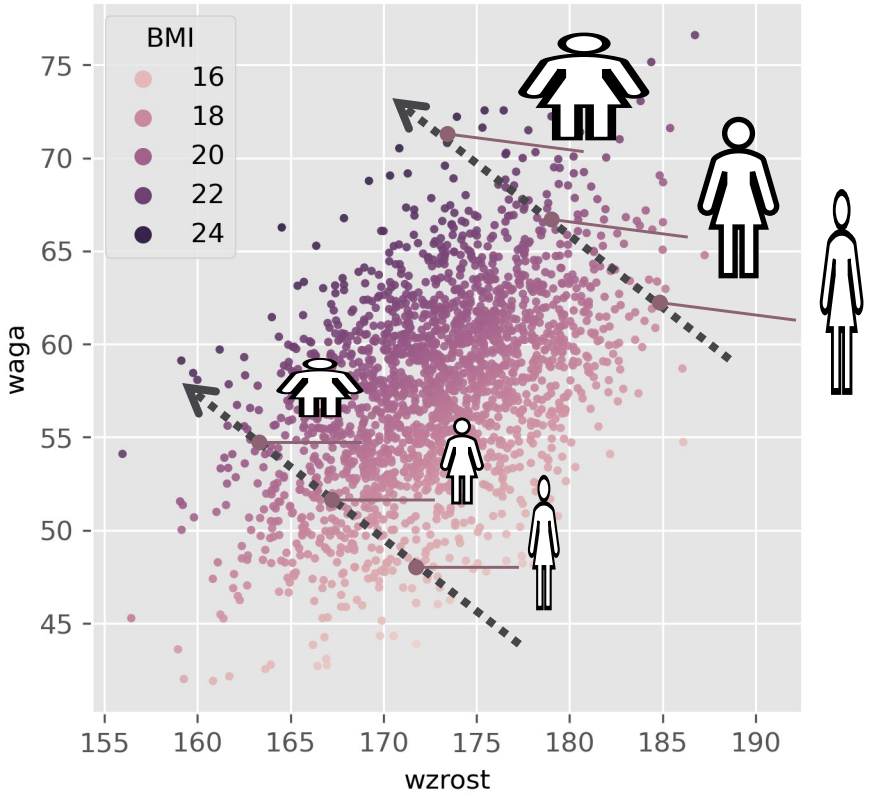

120
Waga
Wzrost
200


175
150
125
100
75
50
25
0
Waga
130
140
150
160
170
180
190
200
Wzrost


175
150
125
100
75
50
25
0
Waga
130
140
150
160
170
180
190
200
Wzrost

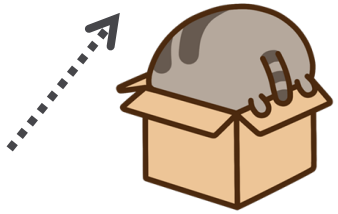

175
150
125
100
75
50
25
0
Waga
130
140
150
160
170
180
190
200
Wzrost

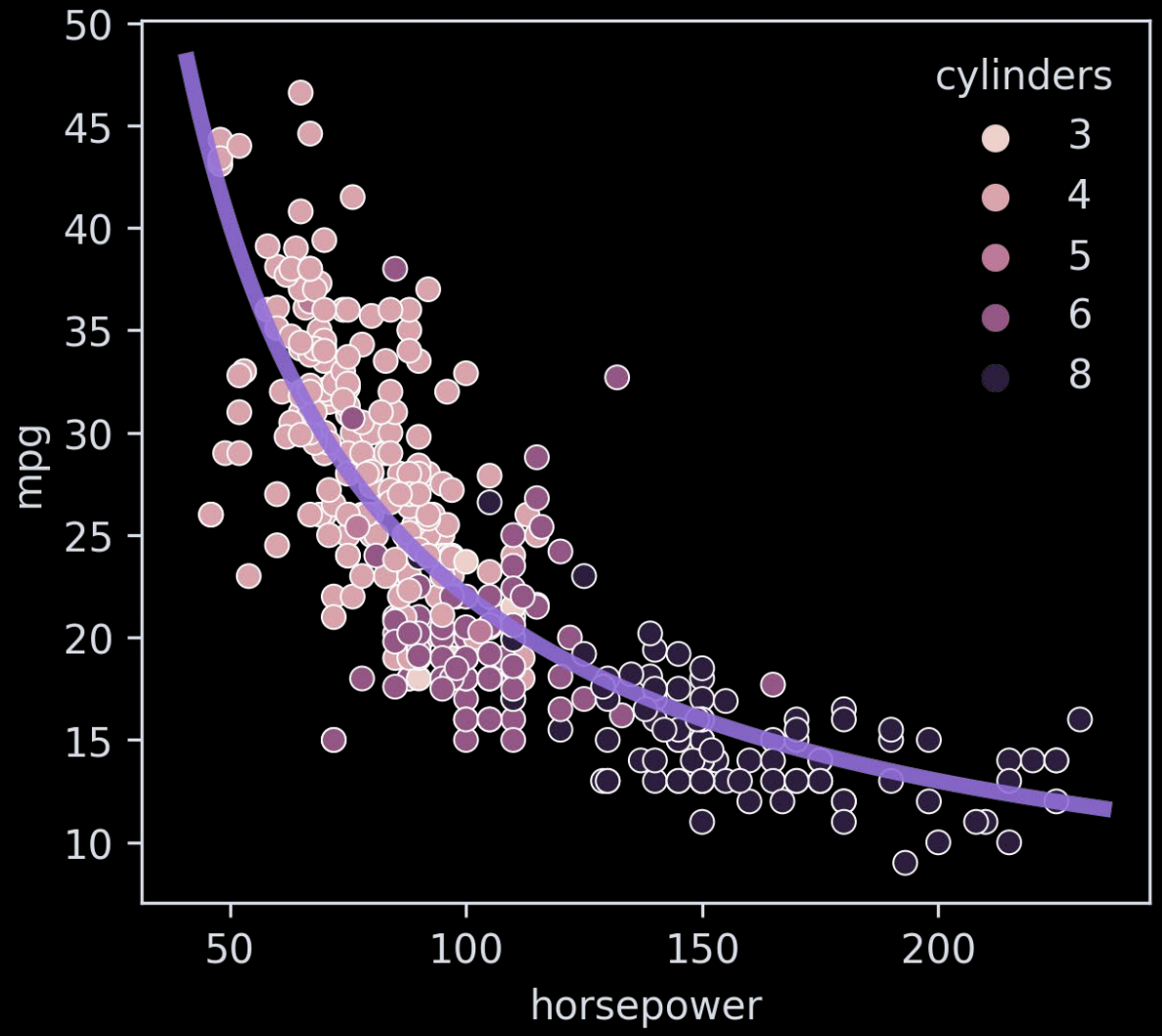


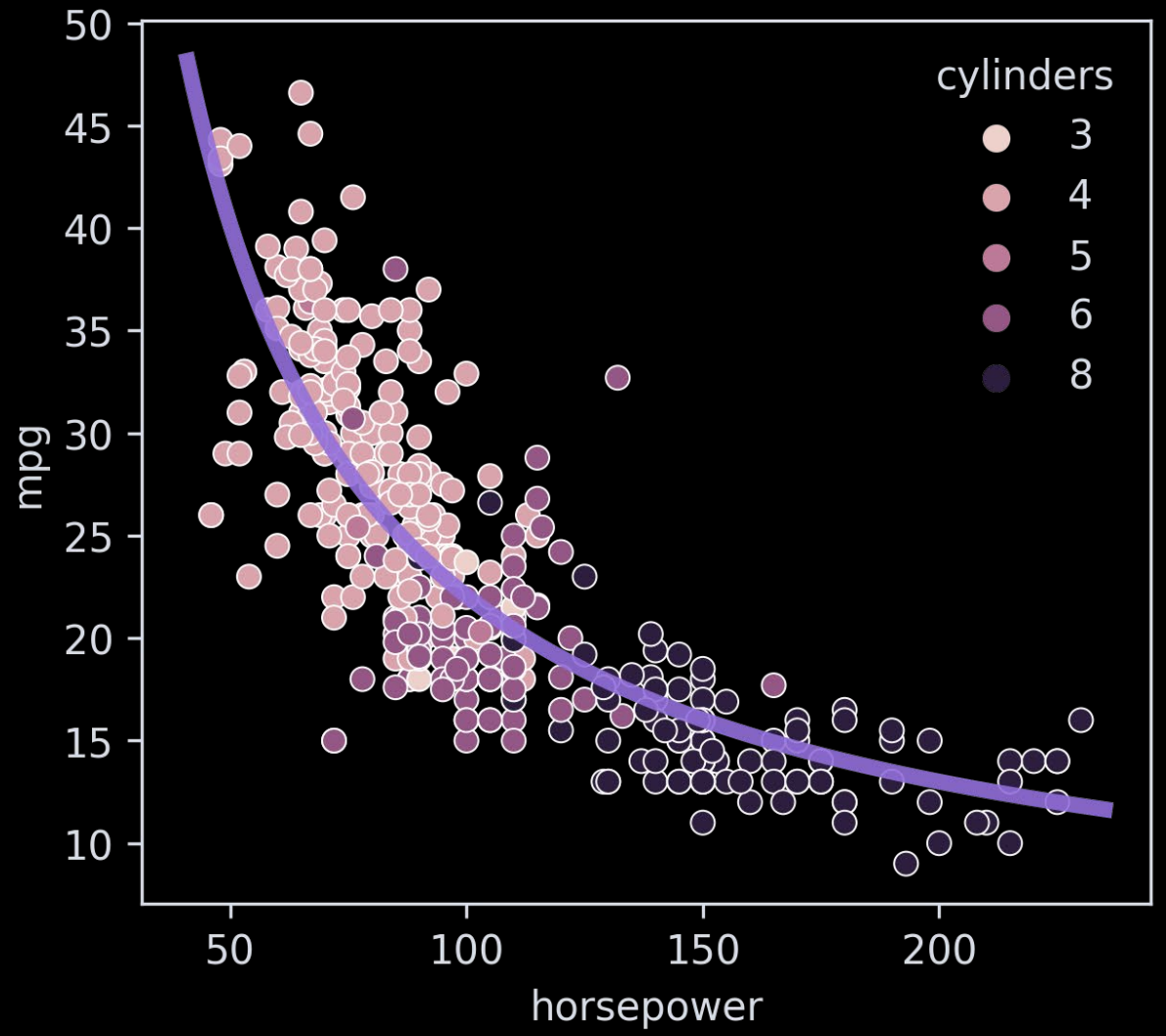


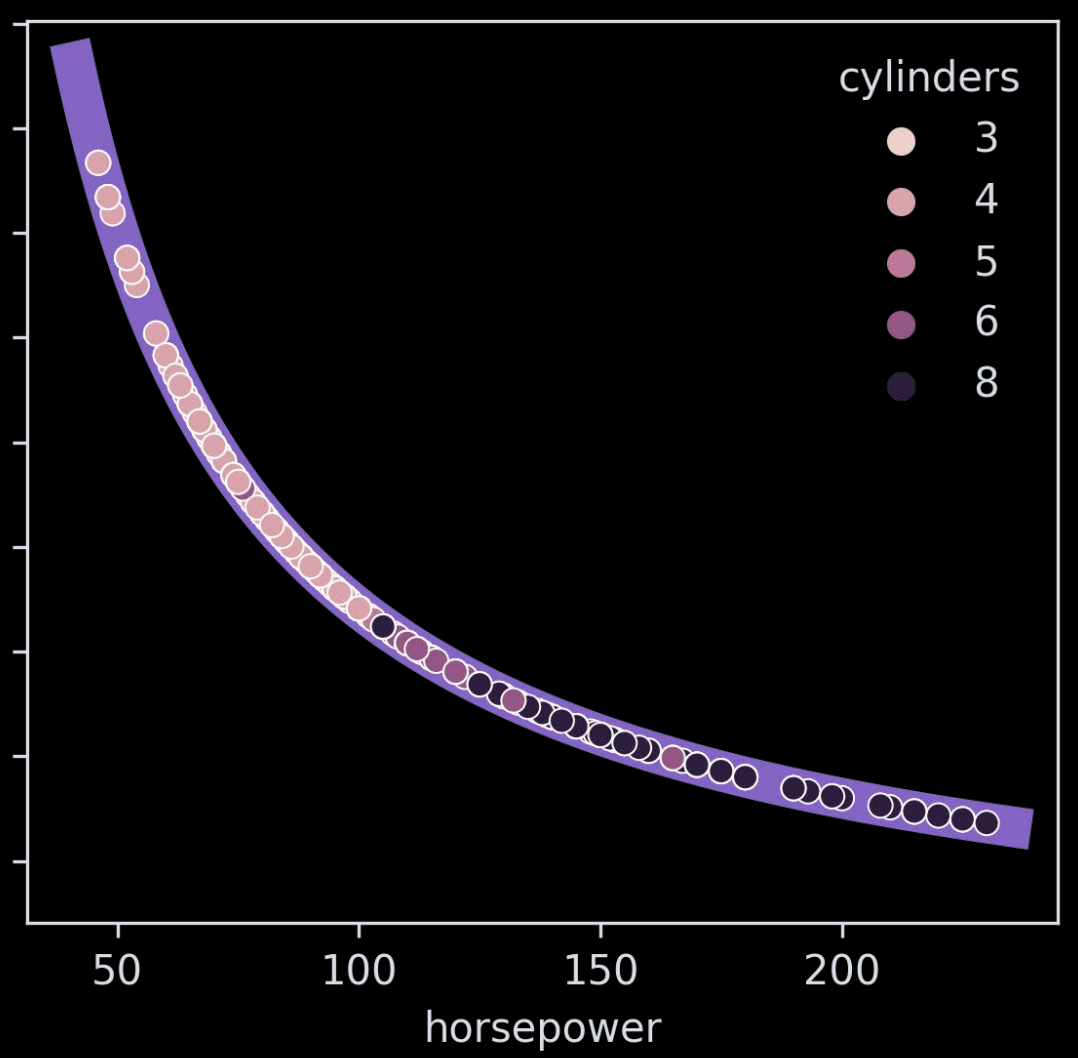
Przestrzeń osadzeń

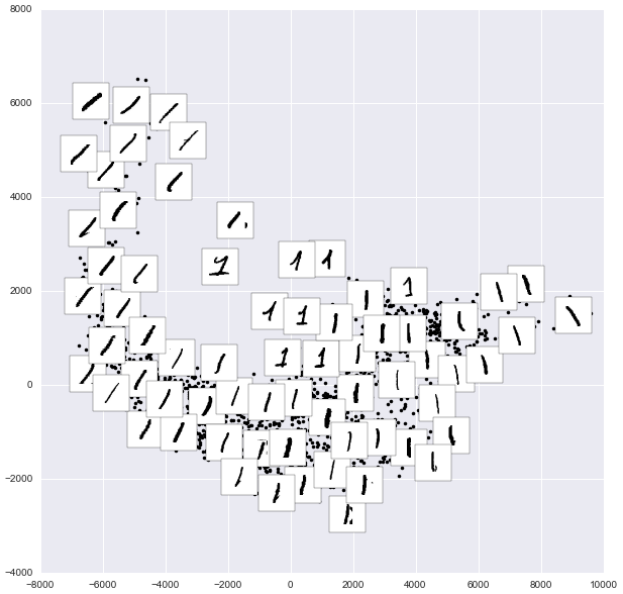
(ang. *latent space*)




cylinders
3
4
5
6
8
mpg
horsepower
50
45
40
35
30
25
20
15
10
50
100
150
200

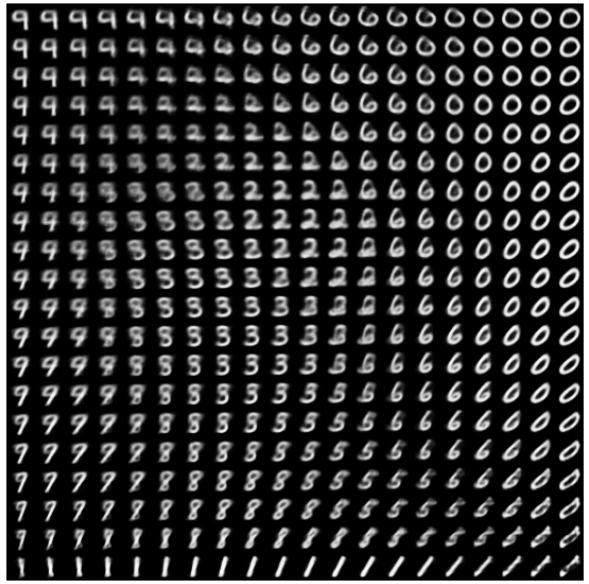

mpg
horsepower
cylinders
3
4
5
6
8
50
45
40
35
30
25
20
15
10
50
100
150
200

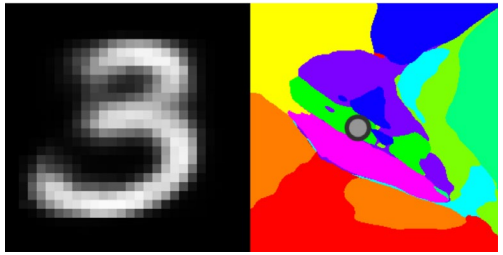

horsepower
cylinders
3
4
5
6
8
50
100
150
200



https://jakevdp.github.io/PythonDataScienceHandbook/

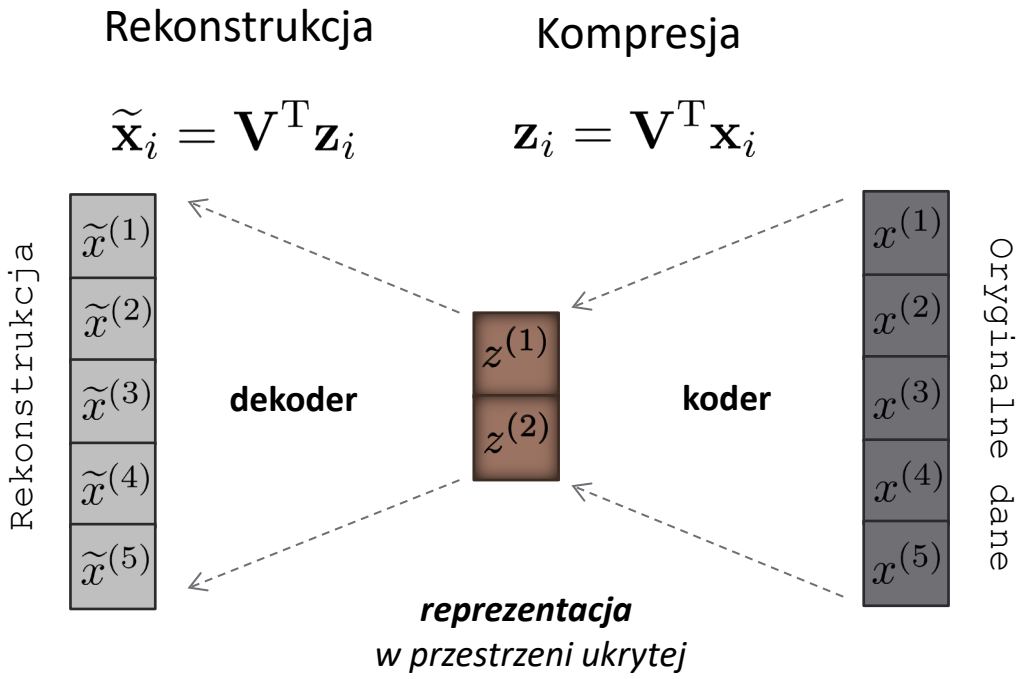
https://n8python.github.io/mnistLatentSpace/





Coś takiego już było...

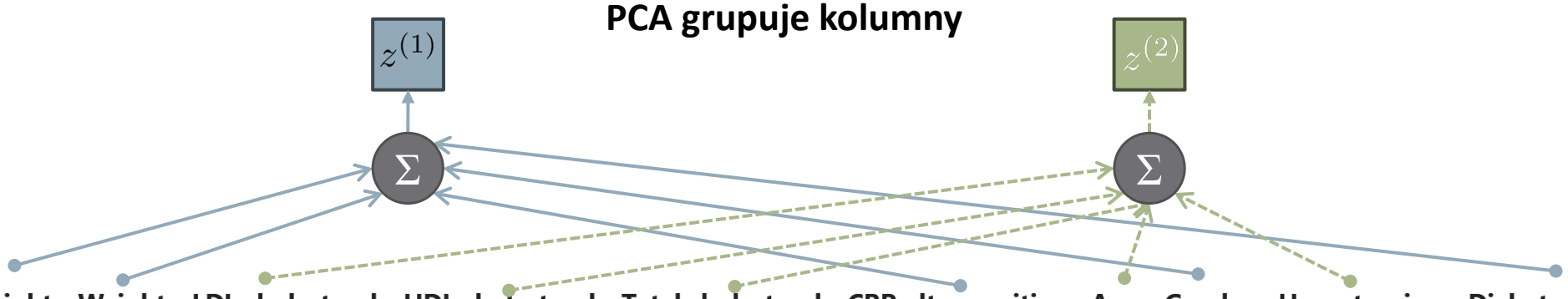
Schemat koder – dekoder



PCA minimalizuje błąd rekonstrukcji

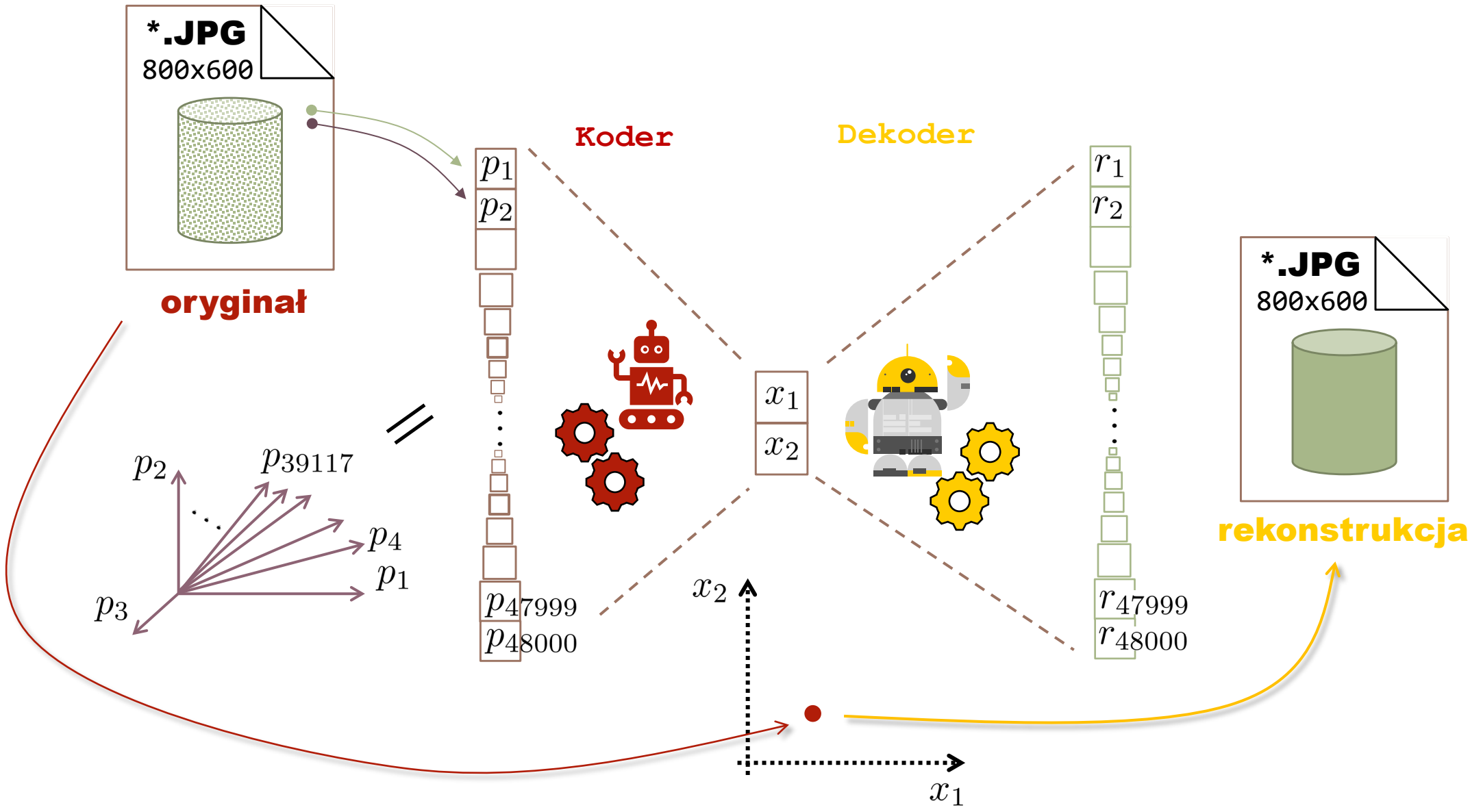
$$\sum_i ||\mathbf{x}_i - \widetilde{\mathbf{x}}_i||_2^2$$

PCA grupuje kolumny

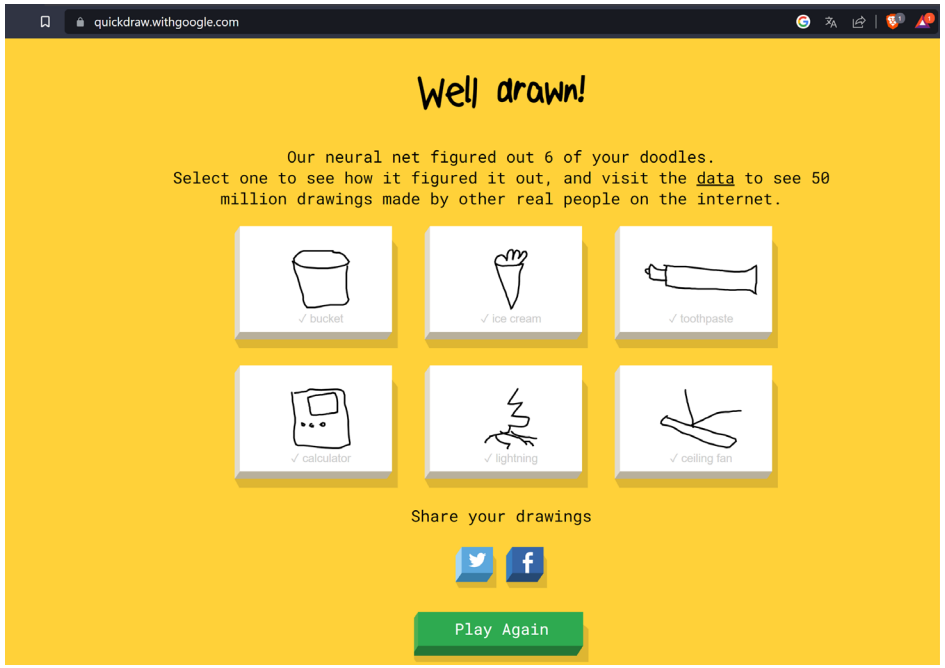


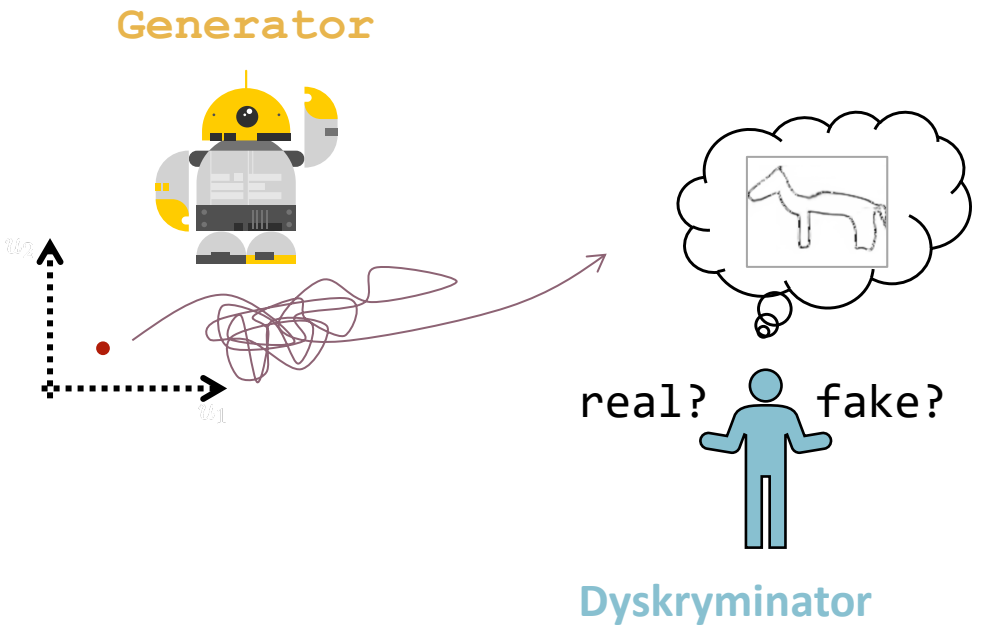
	Height	Weight	LDL cholesterol	HDL cholesterol	Total cholesterol	CRP ultrasensitive	Age	Gender	Hypertension	Diabetes mellitus	
140	182	85	76	47	138	2.14	86	Male	Yes	Yes	
89	177	110	85	45	150	8.04	72	Male	Yes	Yes	
448	164	110	120	37	172	10.98	77	Female	Yes	No	
453	156	70	105	28	162	8.88	89	Female	Yes	Yes	
6	174	100	53	25	96	21.44	81	Male	No	No	
84	185	80	68	36	119	3.77	68	Male	Yes	Yes	
561	170	83	84	34	136	16.42	71	Male	Yes	Yes	
659	170	70	41	33	85	1.17	80	Male	Yes	No	
289	176	85	83	58	155	9.53	53	Male	No	No	
372	160	64	82	53	162	0.92	85	Female	Yes	No	
632	176	107	84	48	150	19.30	56	Male	No	Yes	
132	161	68	25	54	109	1.28	83	Female	Yes	Yes	
379	169	126	8	30	69	6.49	67	Male	Yes	Yes	

Grupowanie grupuje dane


*.JPG
800x600
oryginał
Koder
Dekoder
p_1
p_2
p_{47999}
p_{48000}
x_1
x_2
r_1
r_2
r_{47999}
r_{48000}
p_2
p_{39117}
p_4
p_1
p_3
x_2
x_1
*.JPG
800x600
rekonstrukcja

Przykłady


quickdraw.withgoogle.com
Well drawn!
Our neural net figured out 6 of your doodles.
Select one to see how it figured it out, and visit the data to see 50 million drawings made by other real people on the internet.
✓ bucket
✓ ice cream
✓ toothpaste
✓ calculator
✓ lightning
✓ ceiling fan
Share your drawings
Play Again

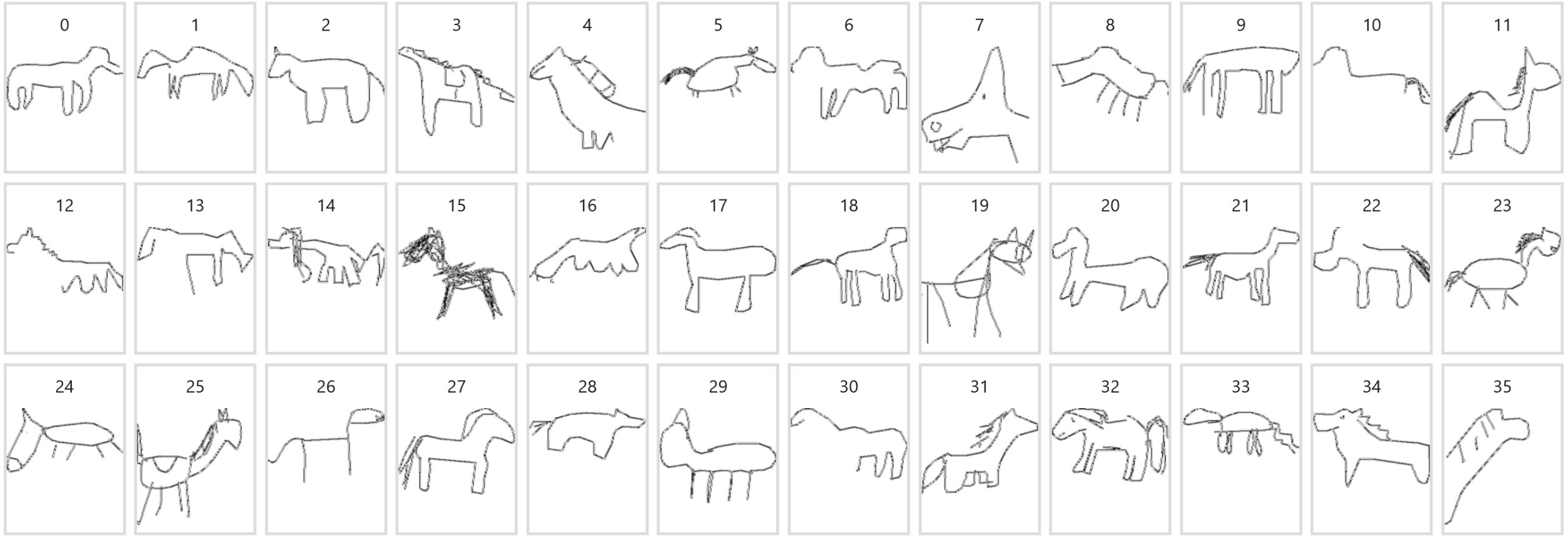

Generator
real?
fake?
Dyskryminator

Dane źródłowe - przykładowe

```
n_samples, width, height = dataset.shape
n_samples, width, height
```

```
(2048, 128, 128)
```

2048 obrazków 128x128 px

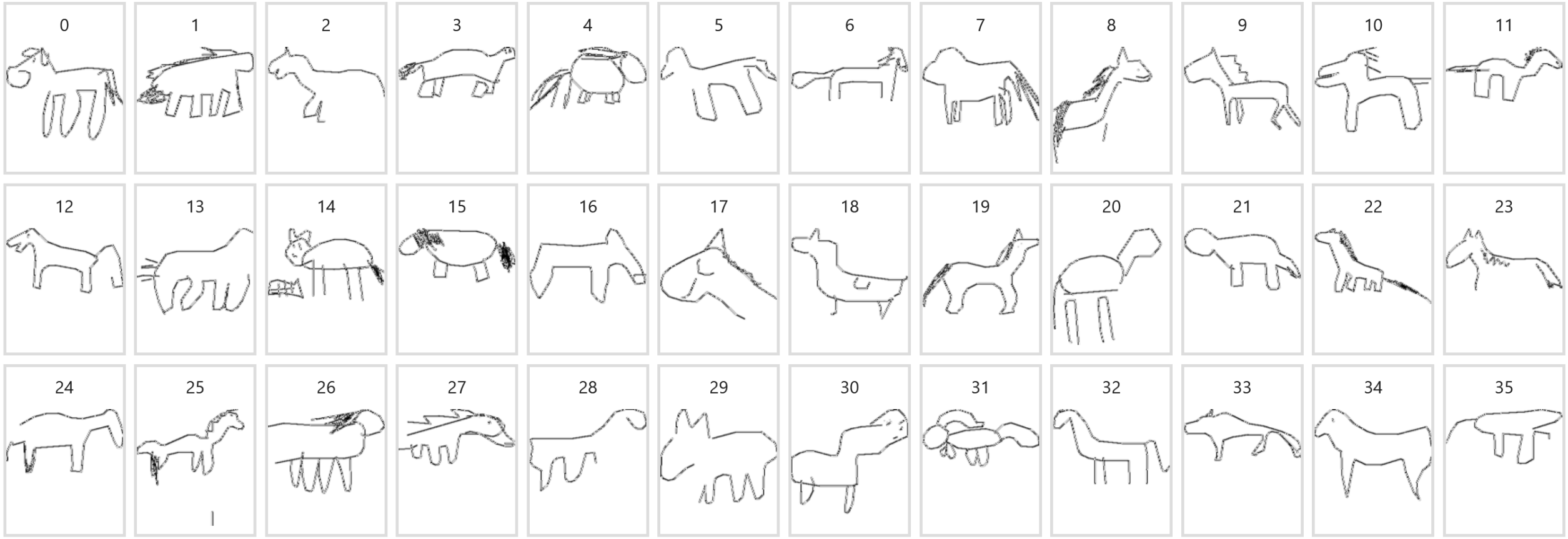


Dane źródłowe - przykładowe

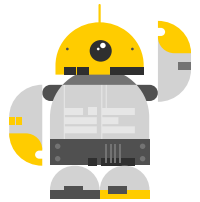
2048 obrazków 128x128 px

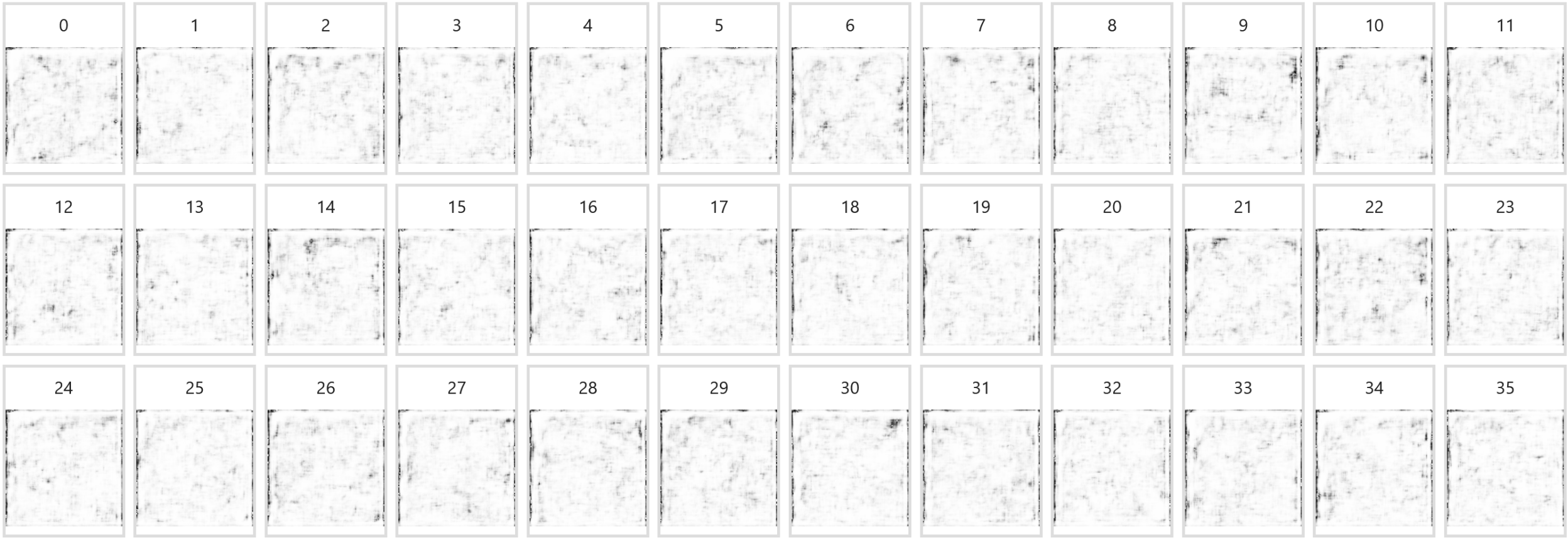
```
n_samples, width, height = dataset.shape
n_samples, width, height
```

```
(2048, 128, 128)
```



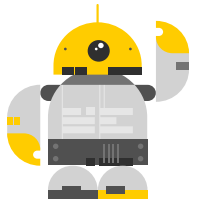
Epoka 1 – produkcje generatora

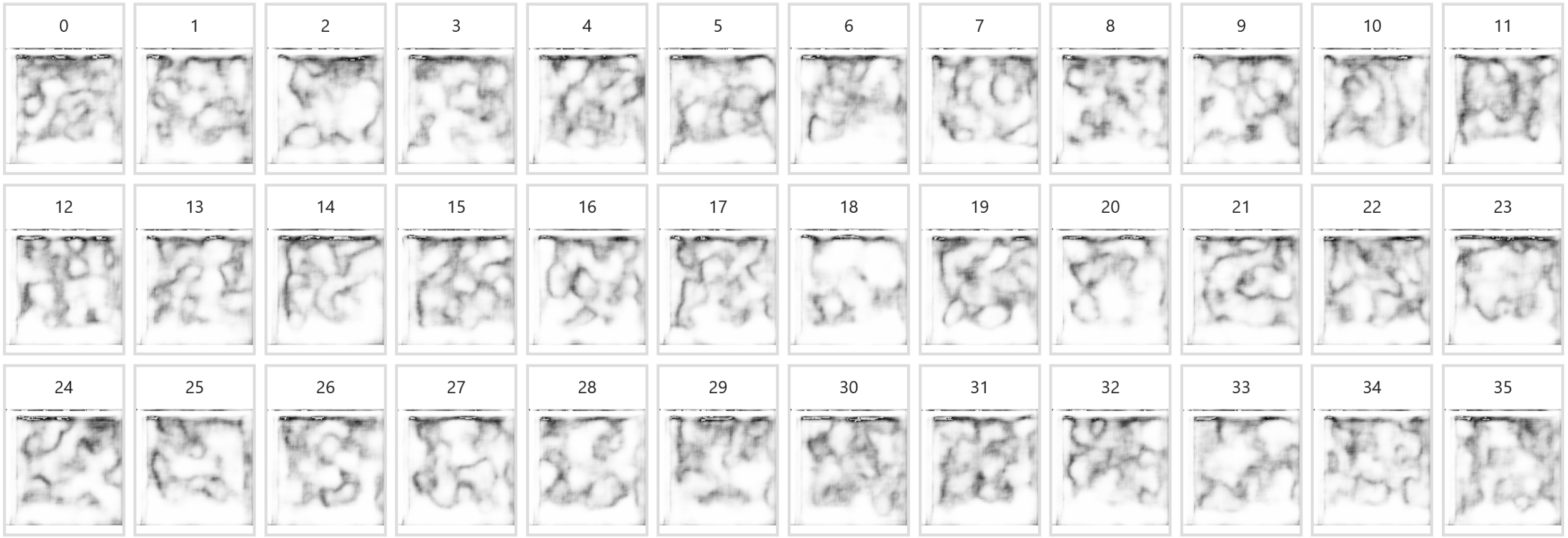




Wymiar przestrzeni osadzeń: 128

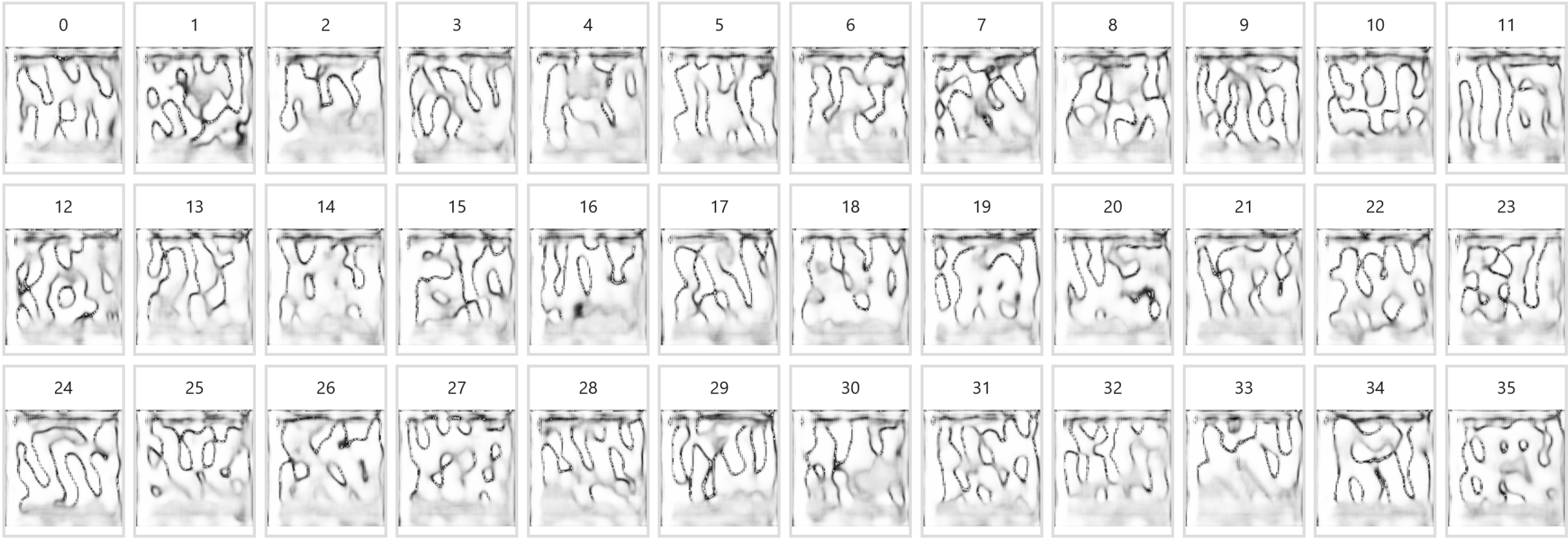
Epoka 2 – produkcje generatora





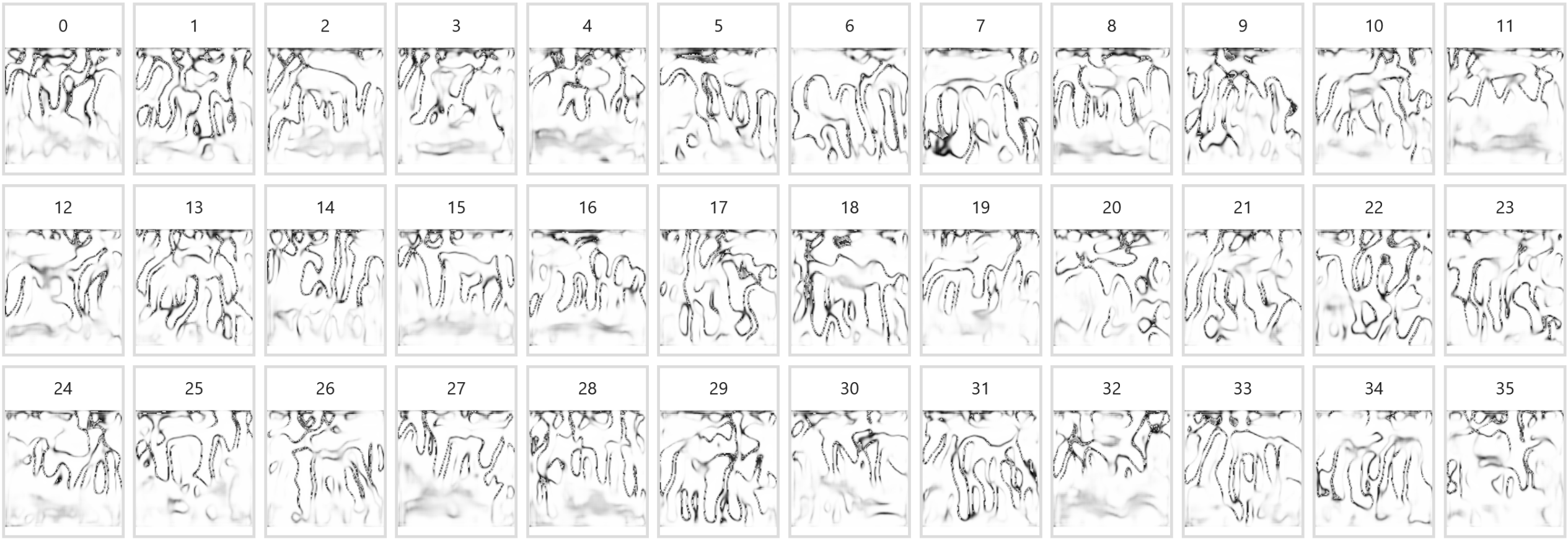
Wymiar przestrzeni osadzeń: 128

Epoka 4 – produkcje generatora



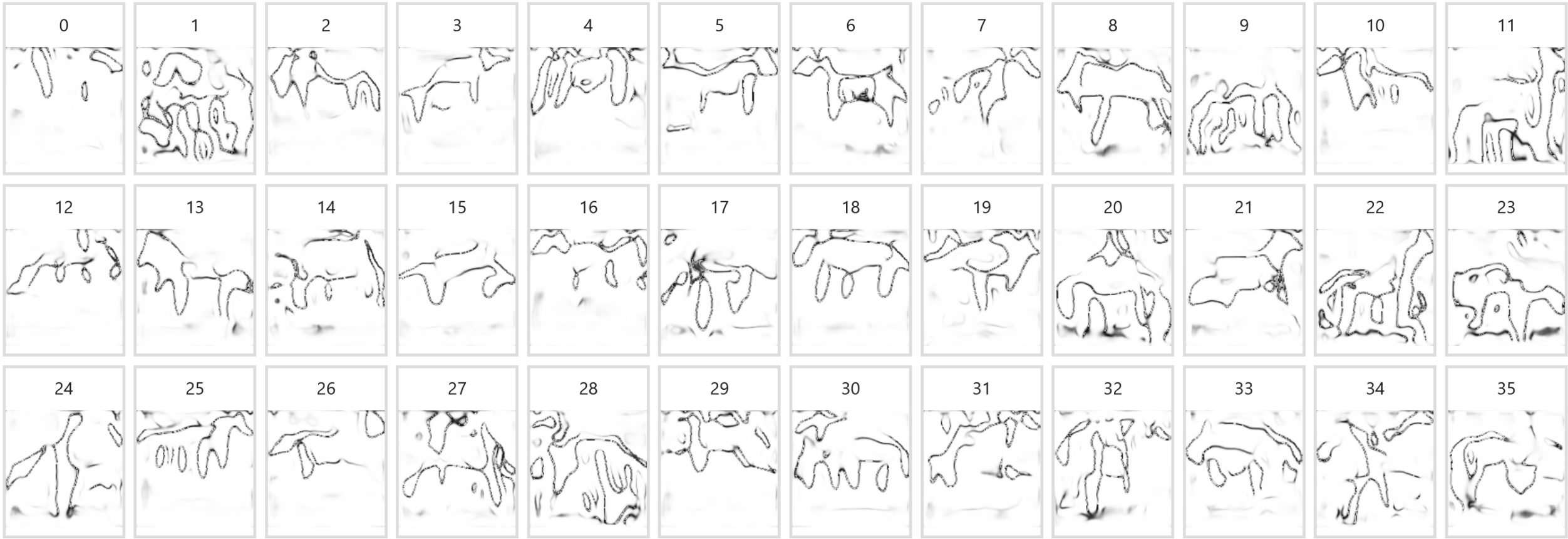
Wymiar przestrzeni osadzeń: 128

Epoka 8 – produkcje generatora



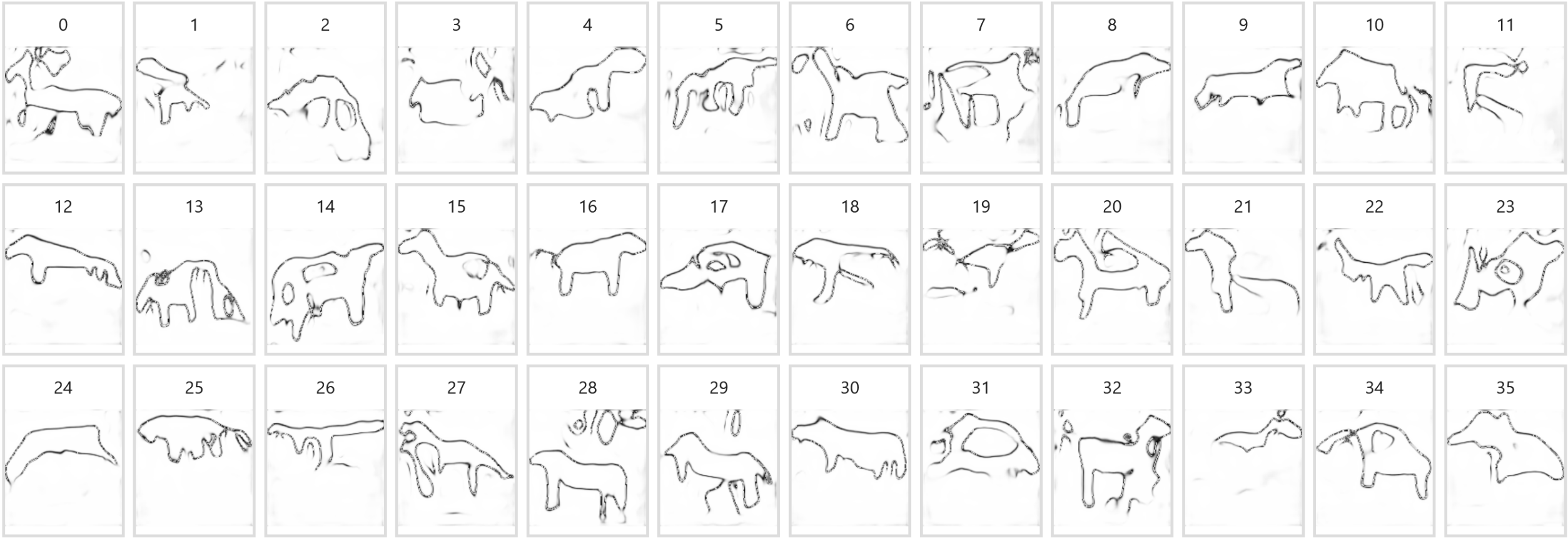
Wymiar przestrzeni osadzeń: 128

Epoka 16 – produkcje generatora



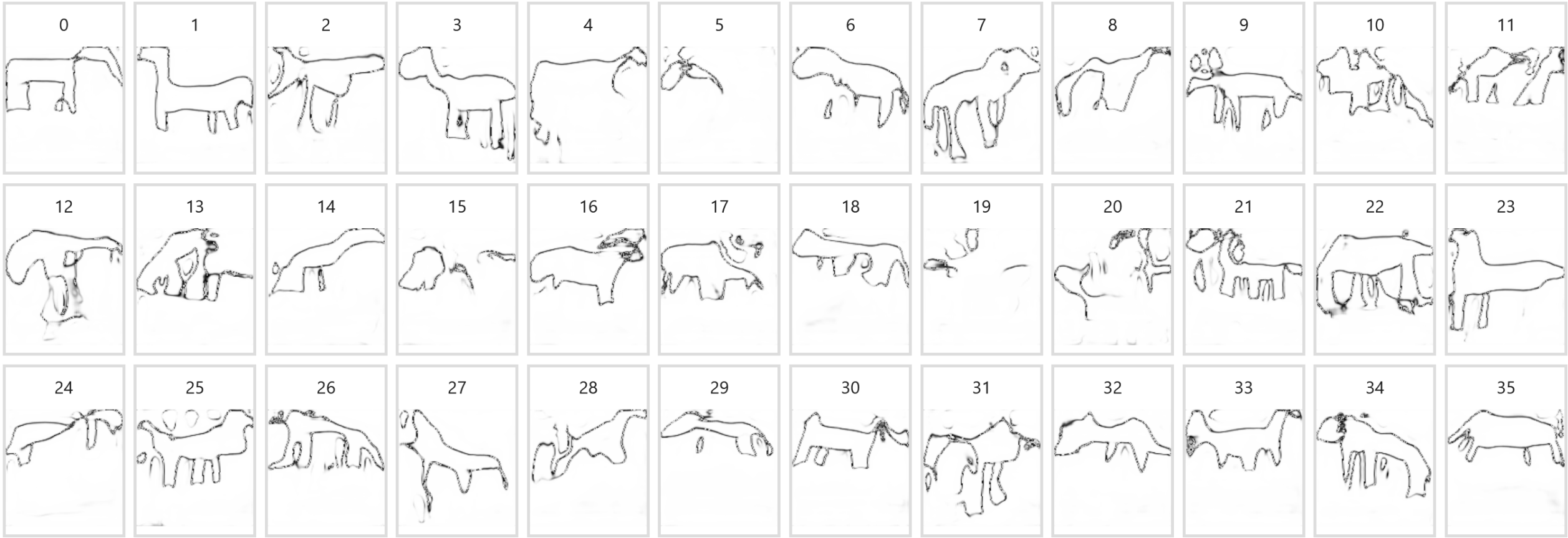
Wymiar przestrzeni osadzeń: 128

Epoka 24 – produkcje generatora



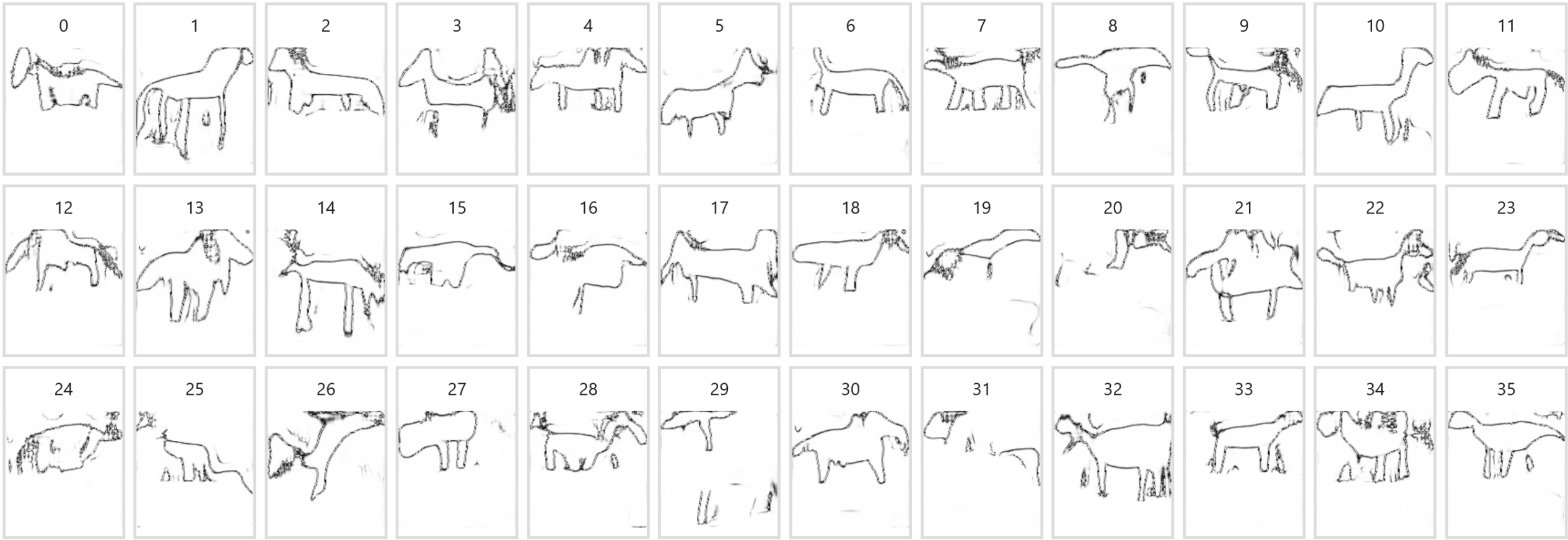
Wymiar przestrzeni osadzeń: 128

Epoka 64 – produkcje generatora



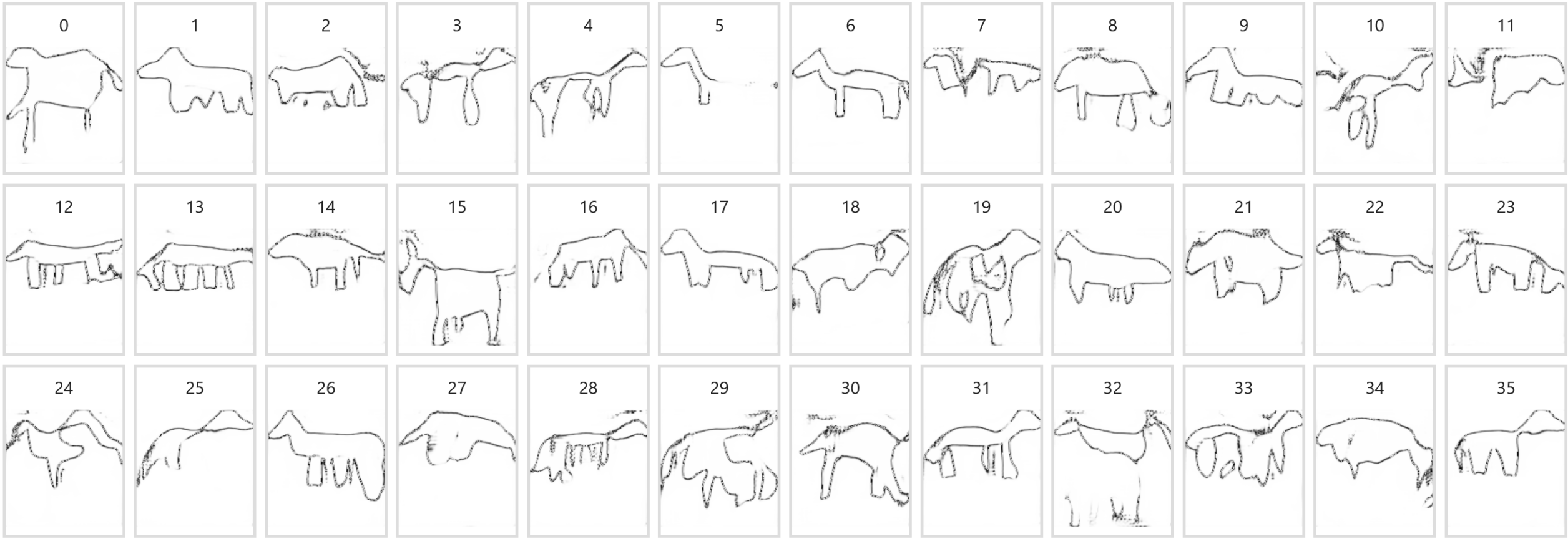
Wymiar przestrzeni osadzeń: 128

Epoka 100 – produkcje generatora



Wymiar przestrzeni osadzeń: 128

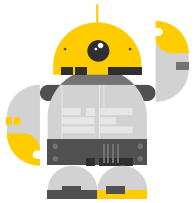
Epoka 150 – produkcje generatora

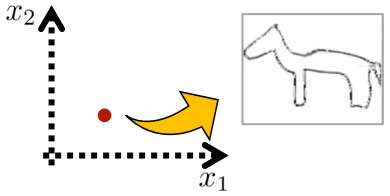


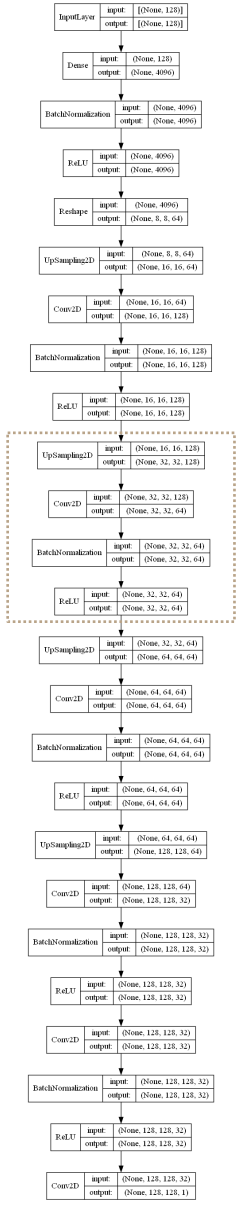
Wymiar przestrzeni osadzeń: 128

GAN

Generator



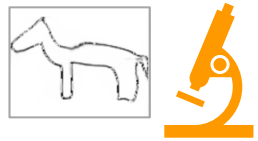




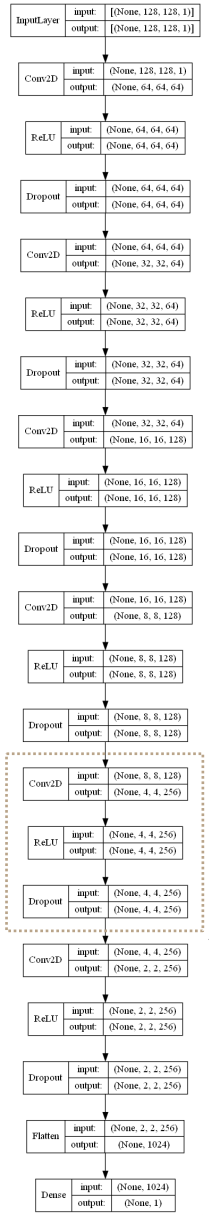
```
Total params: 1,135,969
Trainable params: 1,127,137
Non-trainable params: 8,832
```

UpSampling2D	input:	(None, 32, 32, 64)
	output:	(None, 64, 64, 64)
Conv2D	input:	(None, 64, 64, 64)
	output:	(None, 64, 64, 64)
BatchNormalization	input:	(None, 64, 64, 64)
	output:	(None, 64, 64, 64)
ReLU	input:	(None, 64, 64, 64)
	output:	(None, 64, 64, 64)

Dyskryminator

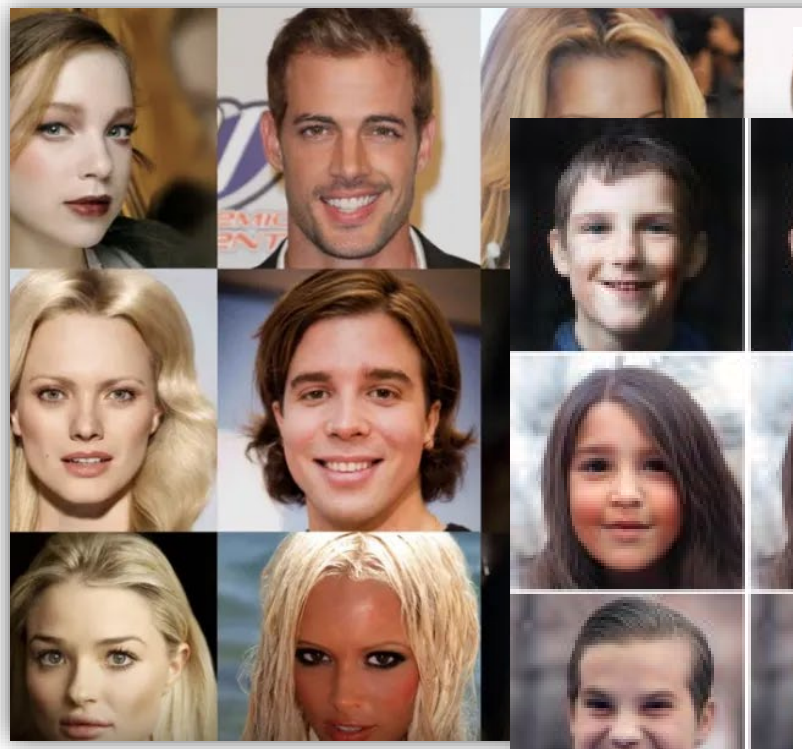


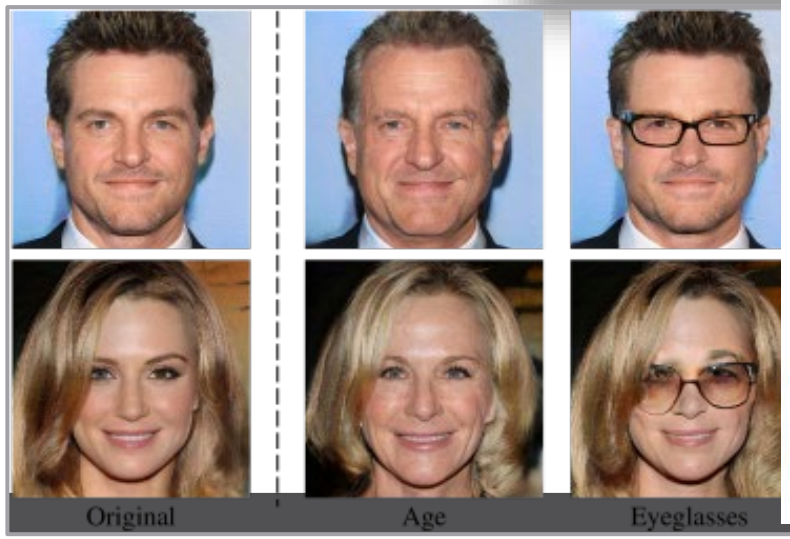
real ? fake



```
Total params: 3,177,921
Trainable params: 0
Non-trainable params: 3,177,921
```

Conv2D	input:	(None, 32, 32, 64)
	output:	(None, 16, 16, 128)
ReLU	input:	(None, 16, 16, 128)
	output:	(None, 16, 16, 128)
Dropout	input:	(None, 16, 16, 128)
	output:	(None, 16, 16, 128)





(a) synthesizing face images with identical w_1 but different w_2.

(b) round face → thin face

(c) no simile → simile

(d) hair → more hair

(e) hair → almost no hair

(f) adult → teenager

(g) pose

(h) male → female

(i) no hat → hat

Fig. 1: Attribute editing using the propsed STGAN-WO. (a) generating face images using identical w_1 but different w_2. Hence, all the faces share identical face shapes, *i.e.*, the texture component, and have different structure parts. (b)-(i) synthesizing face images using identical w_2 but different w_1. Moving the intermediate latent code w_1 along its orthogonal directions can achieve the goal of attribute editing such that some specific attribites can be changed indivually.

Premierowi się nie odmawia.

Dali jej do ręki różaniec, więc go odmówiła.

Pocisk zniszczył domek, bo był z papieru. Co było z papieru: pocisk czy domek?

Do jakiej litery jest podobna obrócona litera p?

$$\begin{bmatrix} 0.4 \\ 0.11 \\ 0.82 \\ 0.73 \end{bmatrix} \quad \begin{bmatrix} 0.71 \\ 0.03 \\ 0.11 \\ 0.65 \end{bmatrix} \quad \begin{bmatrix} 0.21 \\ 0.13 \\ 0.31 \\ 0.92 \end{bmatrix}$$

osadzenia słów

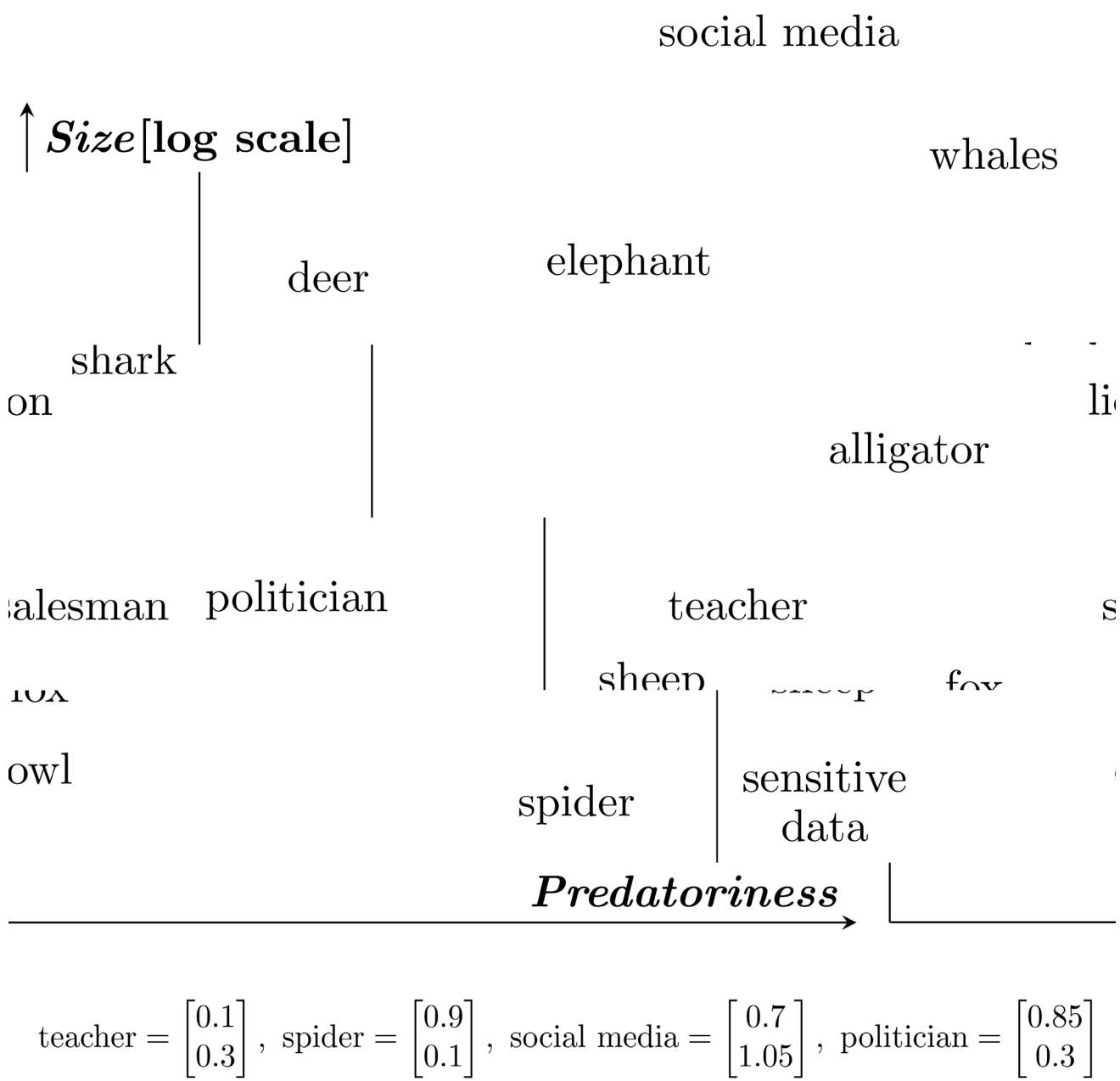
(ang. *embeddings*)

The prime minister is not denied.

They gave her a rosary and she refused it.

The bullet destroyed the house because it was made of paper. What was paper: a bullet or a house?

What letter is the rotated p similar to?



$$\text{teacher} = \begin{bmatrix} 0.1 \\ 0.3 \end{bmatrix}, \ \text{spider} = \begin{bmatrix} 0.9 \\ 0.1 \end{bmatrix}, \ \text{social media} = \begin{bmatrix} 0.7 \\ 1.05 \end{bmatrix}, \ \text{politician} = \begin{bmatrix} 0.85 \\ 0.3 \end{bmatrix}$$

$$\text{teacher} + \text{spider} = \text{politician}$$

You

Beef - cow + pig

ChatGPT

If you subtract a cow from beef and add a pig, you get pork!