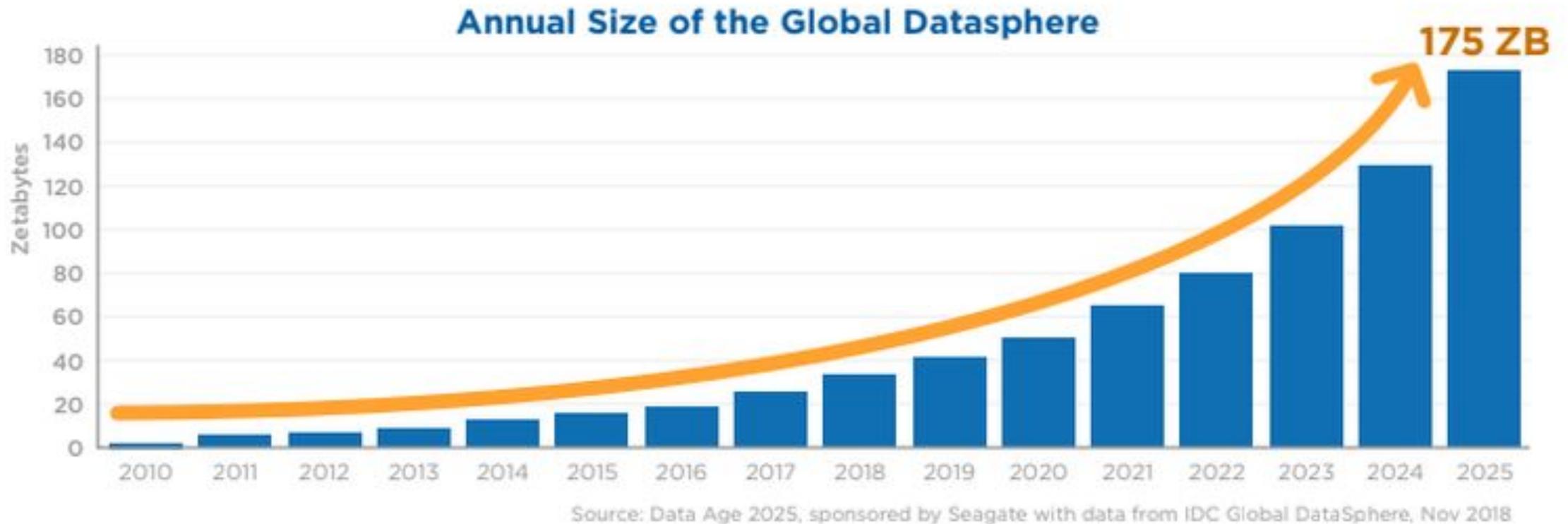


Основы Data science

Кластеризация

- **Data Science** — это работа с большими данными (*англ. Big Data*).

Figure 1 - Annual Size of the Global Datasphere



1 ZB = 10^{21} bytes

1 TB = 10^{12} bytes

Evolution of a Terabyte of Data 1956 - 2015

A decade by decade guide to storing 1TB of data from the 1950s to 2015

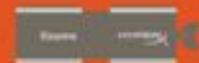


280MB

1960s

1TB

2013



Эволюция
в
области
хранения и
Обработки
данных

Кто такой Data Scientist?

DATA SCIENTIST MUST-HAVE SKILLS

MATH & STATISTICS

- Machine Learning
- Statistical Modeling
- Exploratory Analysis
- Clustering
- Regression Analysis

DOMAIN KNOWLEDGE & SOFT SKILLS

- Inclination towards business operations
- Keen on working with data
- Problem solver
- Strategic, proactive, and cooperative
- Interested in hacking



PROGRAMMING & DATABASE

- Computer Science Fundamentals
- Database Management System
- Data Visualization
- Python
- Big Data

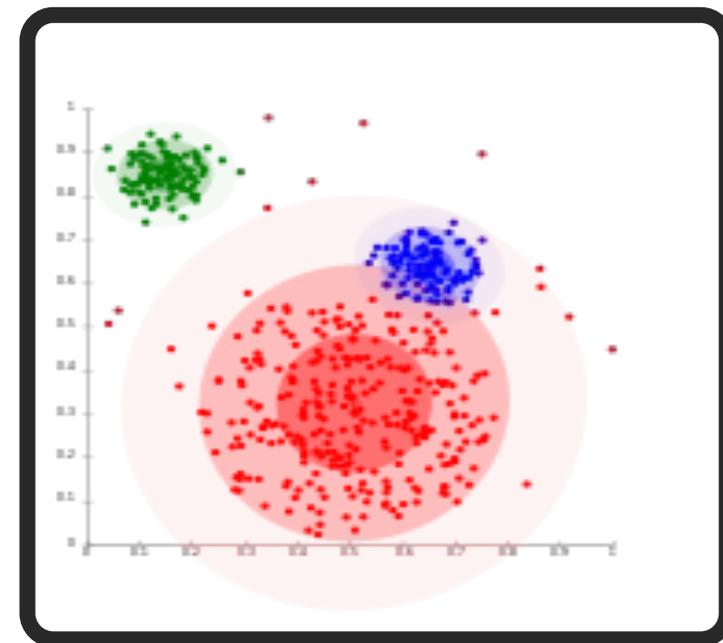
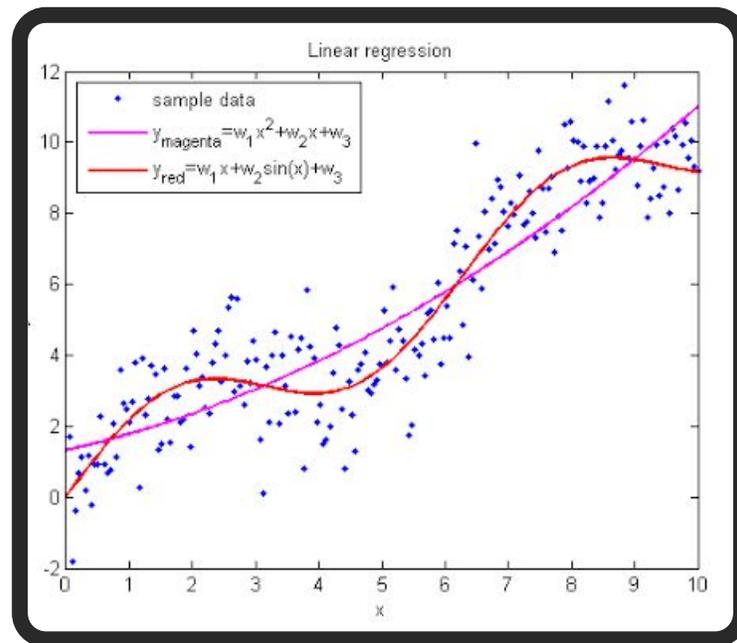
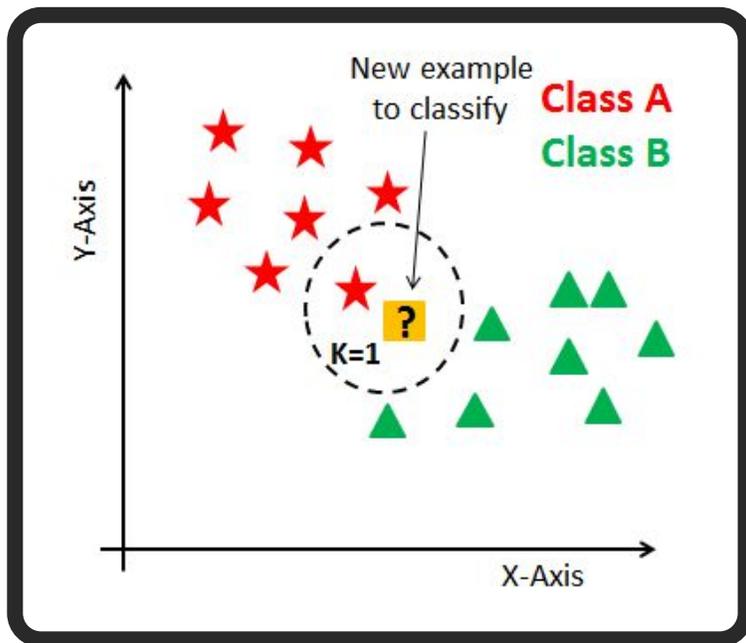
COMMUNICATION & VISUALIZATION

- Storytelling skills
- Convert data-based insights into decisions
- Collaborative with Sr. Management
- Knowledge of tools like Tableau
- Visual art design

Классификация

Регрессия

Кластеризация



Независимые переменные

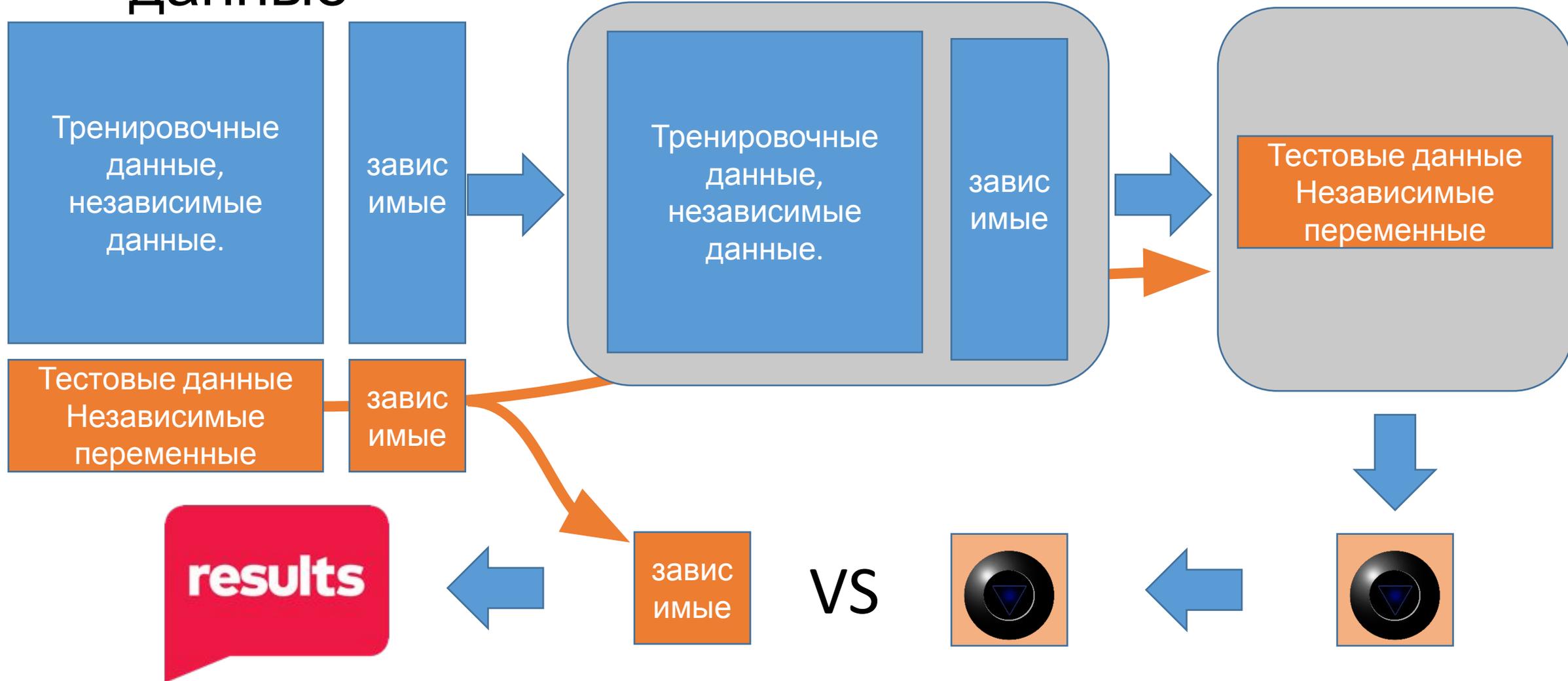
V - 1	V - 2	V - 3	V - 4	V - 5	V - 6	V - 7	V - 8	V - 9	V - 10
value									
value									
value									
value									
value									
value									
value									
value									

Зависимая

Num	Class
1.003	cat
2.008	dog
7.256	dog
8.240	cat
3.001	cat
5.443	cat
2.754	dog
?	?

Исходные данные

Модель МО





Epoch
000,158

Learning rate
0.03

Activation
Tanh

Regularization
None

Regularization rate
0

Problem type
Classification

DATA

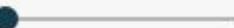
Which dataset do you want to use?



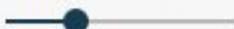
Ratio of training to test data: 50%



Noise: 0



Batch size: 10

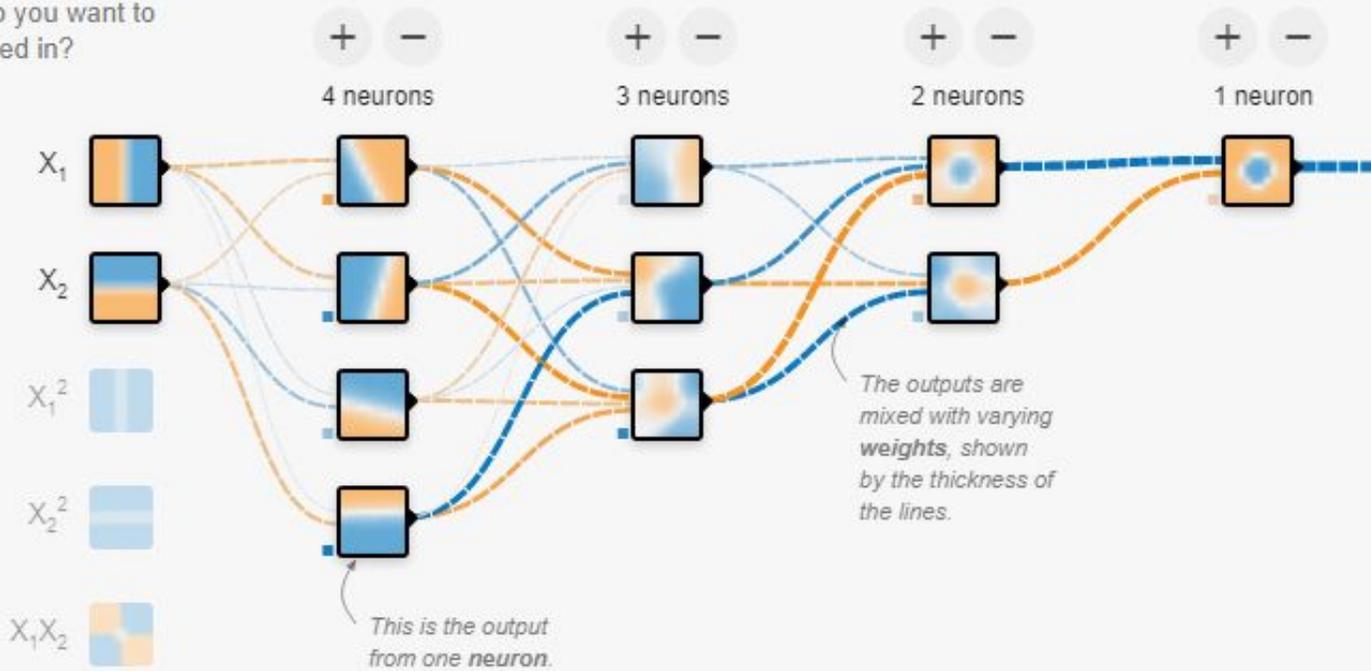


FEATURES

Which properties do you want to feed in?

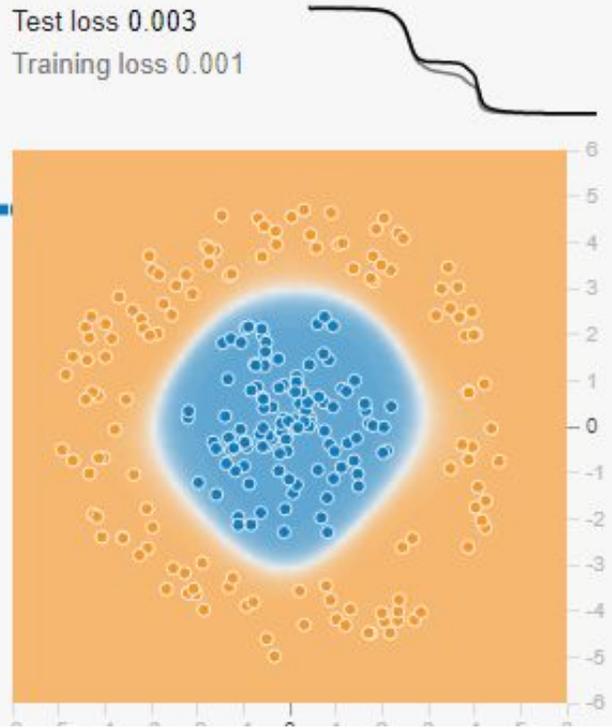
- X_1
- X_2
- X_1^2
- X_2^2
- X_1X_2

+ - 4 HIDDEN LAYERS



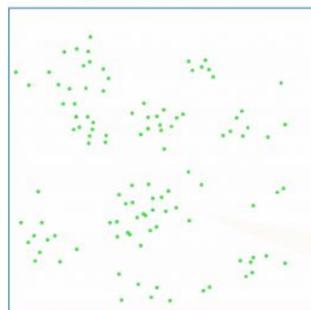
OUTPUT

Test loss 0.003
Training loss 0.001

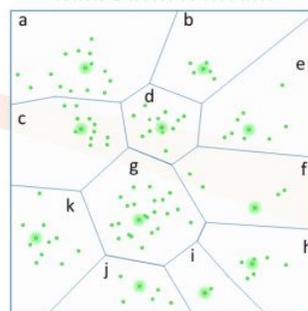


Кластеризация молекул

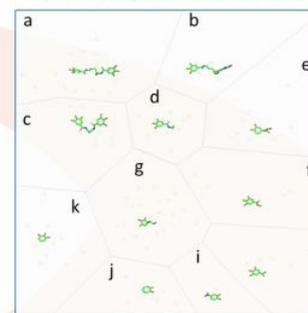
A. Molecules as fingerprints



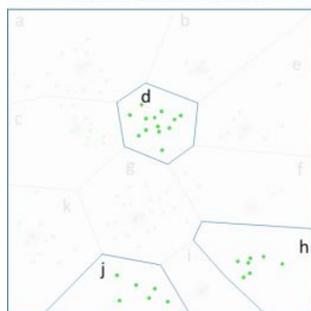
B. Clustering with Mini Batch K-means



C. Virtual Screening with 1 molecule/cluster



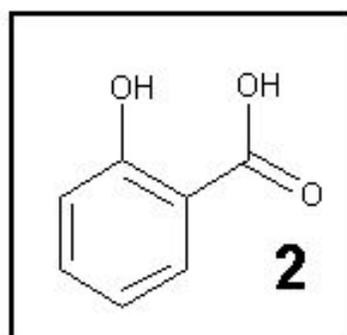
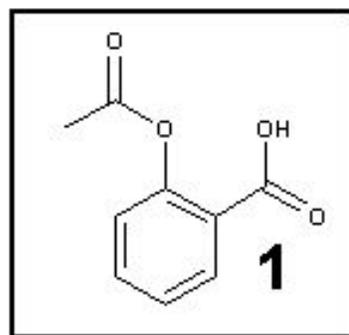
D. Identification of clusters for a second Virtual Screening



PharmScreen

	Cluster	Alignment	Score
Selected	h		0.87
	d		0.85
	j		0.81
	b		0.73
	k		0.69
	e		0.68
	f		0.62
	a		0.55
	i		0.50
	c		0.47
	g		0.46

Similarity Searching



1	1	1	0	1	1	0	1	0
2	1	1	0	1	0	0	0	0

A = Number of bits set in both = 3

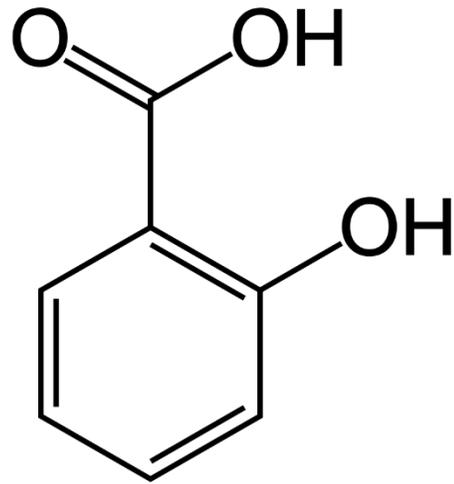
B = Number of bits set in (1), but not in (2) = 2

C = Number of bits set in (2), but not in (1) = 0

$$\text{TANIMOTO COEFFICIENT} = A / (A + B + C)$$

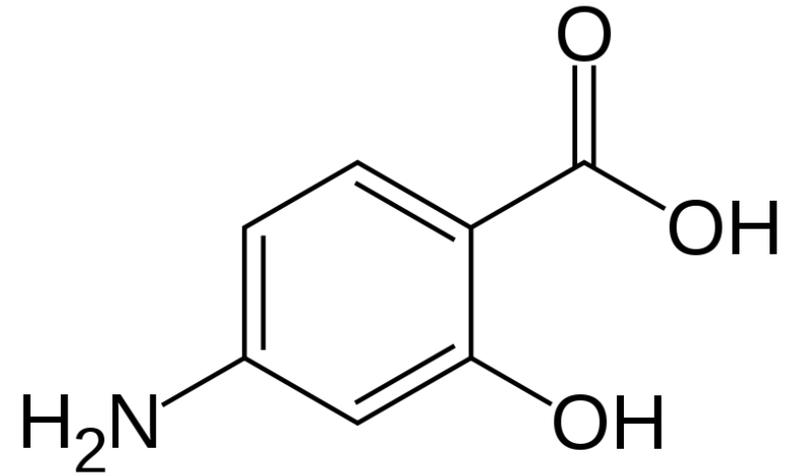
$$= 3 / (3 + 2 + 0) = 0.6 \text{ or } 60\%$$

Задача на Python



Salicylic acid

c1ccc(c(c1)C(=O)O)O



PASA

C1=CC(=C(C=C1N)O)C(=O)O

Tanimoto coefficient, Tanimoto distance

```
In [19]: from rdkit import Chem
         from rdkit.Chem import Descriptors
         from rdkit.Chem import rdFingerprintGenerator
```

```
In [20]: SA = 'c1ccc(c(c1)C(=O)O)O'
         PASA = 'C1=CC(=C(C=C1N)O)C(=O)O'
```

```
In [21]: SA = Chem.MolFromSmiles(SA)
         PASA = Chem.MolFromSmiles(PASA)
```

```
In [22]: rdkit_gen = rdFingerprintGenerator.GetRDKitFPGenerator(maxPath=5)
```

```
In [26]: SA_fp = rdkit_gen.GetFingerprint(SA)
         PASA_fp = rdkit_gen.GetFingerprint(PASA)
```

```
In [33]: sim = round(Chem.DataStructs.TanimotoSimilarity(SA_fp, PASA_fp), 3)
         sim
```

```
Out[33]: 0.811
```

```
In [36]: tanimoto_distance = round(1-sim, 3)
         tanimoto_distance
```

```
Out[36]: 0.189
```

```
data = pd.read_csv('Data_ML.csv')
```

```
compounds = []  
for _, chembl_id, smile in data[['molecule_chembl_id', 'Smiles']].itertuples():  
    compounds.append((Chem.MolFromSmiles(smile), chembl_id))  
compounds[:5]
```

```
[(<rdkit.Chem.rdchem.Mol at 0x280de08e7b0>, 'CHEMBL3640324'),  
(<rdkit.Chem.rdchem.Mol at 0x280de08e530>, 'CHEMBL3640408'),  
(<rdkit.Chem.rdchem.Mol at 0x280de08ee40>, 'CHEMBL3642557'),  
(<rdkit.Chem.rdchem.Mol at 0x280dec69850>, 'CHEMBL3642442'),  
(<rdkit.Chem.rdchem.Mol at 0x280dec693f0>, 'CHEMBL3955760')]
```

```
rdkit_gen = rdFingerprintGenerator.GetRDKitFPGenerator(maxPath=5)  
fingerprints = [rdkit_gen.GetFingerprint(mol) for mol, indx in compounds]
```

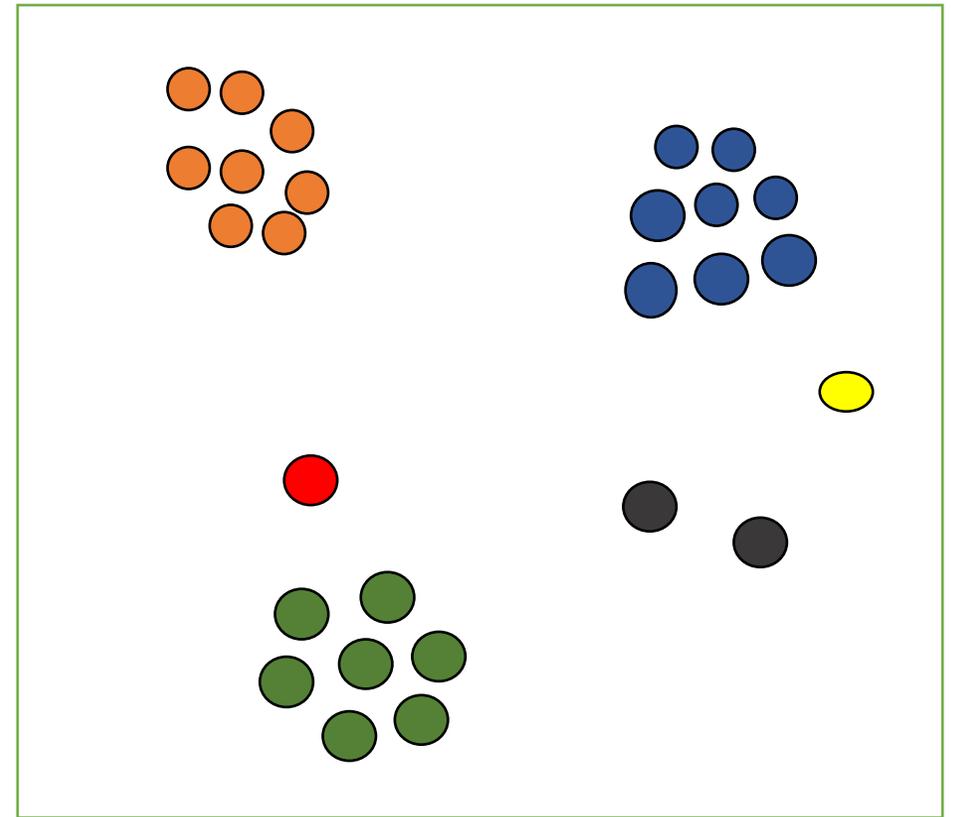
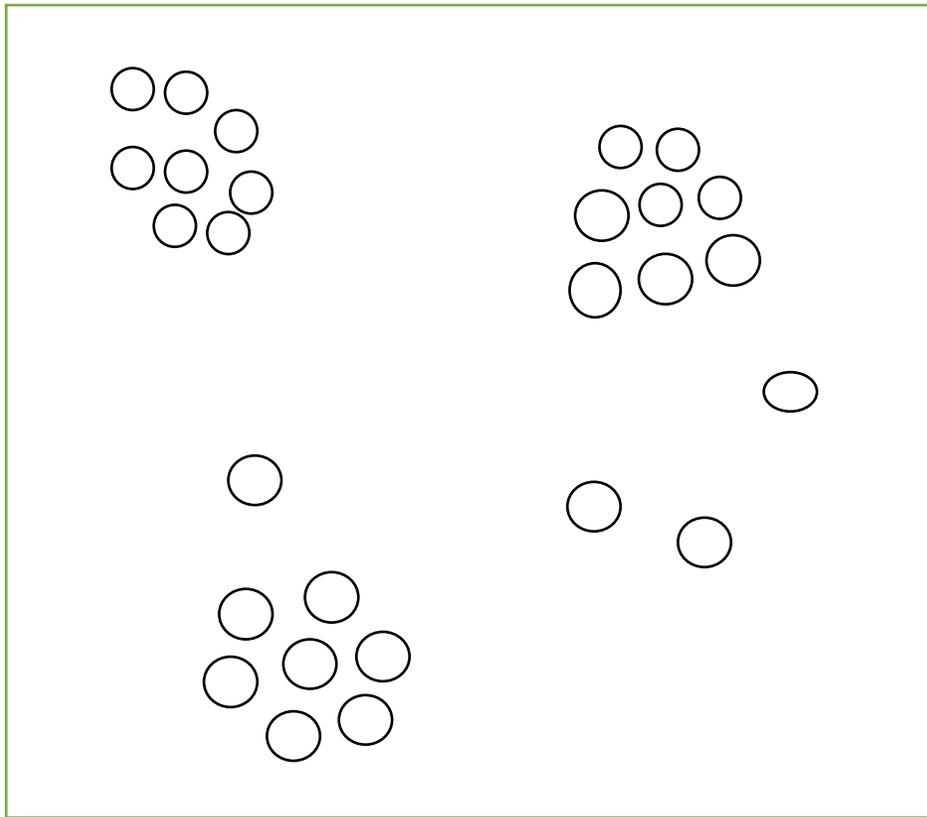
```
fingerprints[0:5]
```


Трудности...

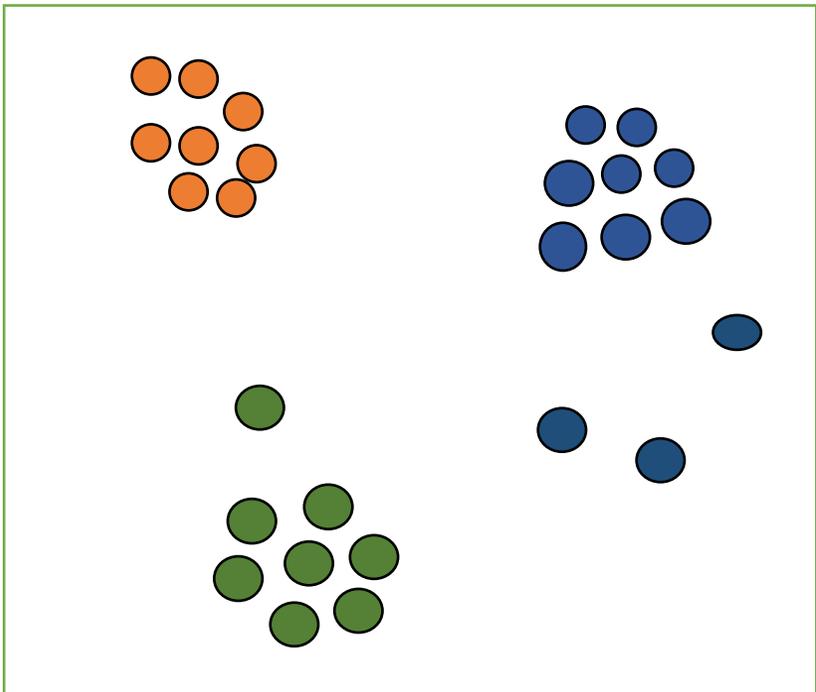
```
def tanimoto_distance_matrix(fp_list):  
    dissimilarity_matrix = []  
    for i in range(1, len(fp_list)):  
        similarities = DataStructs.BulkTanimotoSimilarity(fp_list[i], fp_list[:i])  
        dissimilarity_matrix.extend([1 - x for x in similarities])  
    return dissimilarity_matrix
```

```
tdm = tanimoto_distance_matrix(fingerprints)
```

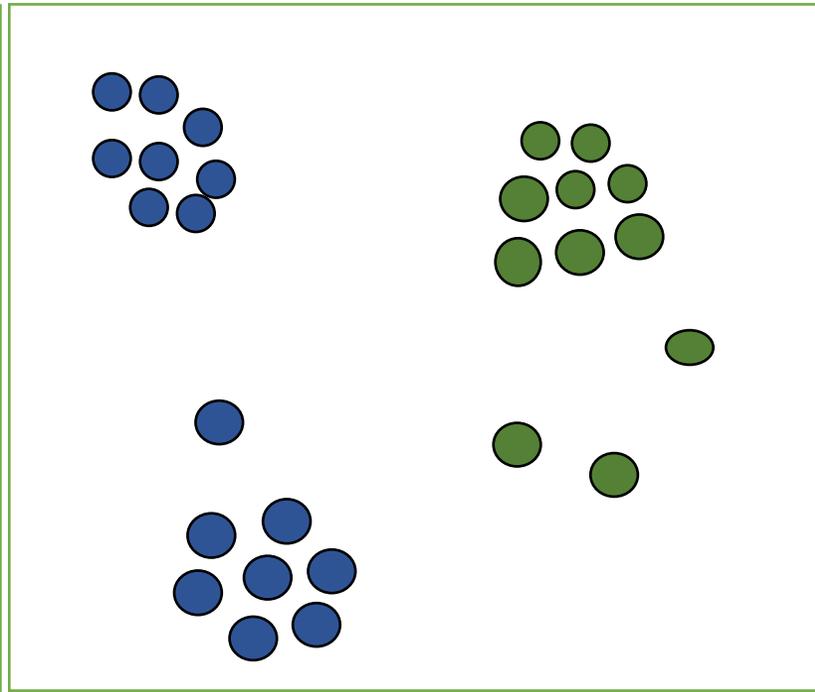
Принцип кластеризации



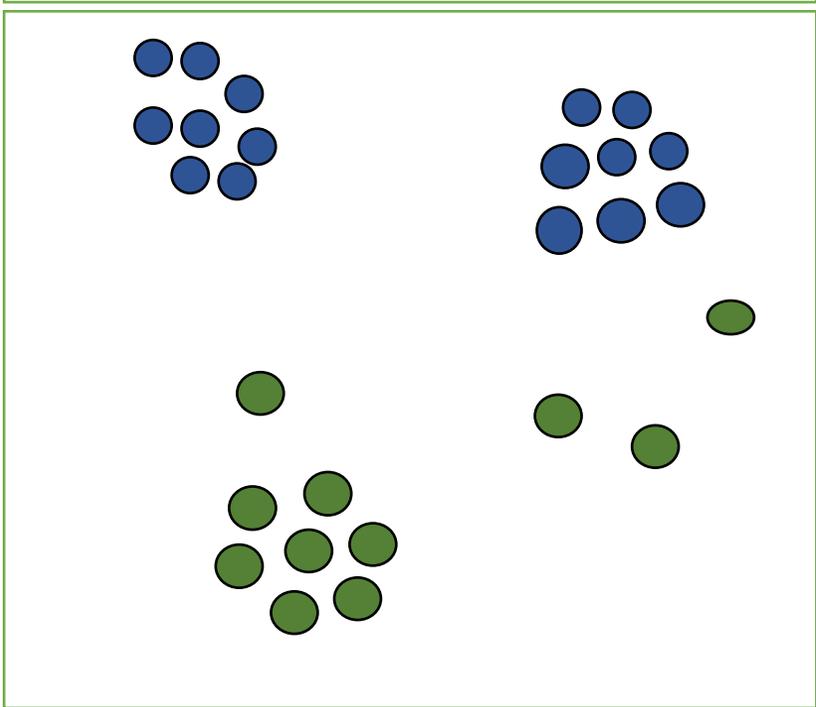
A



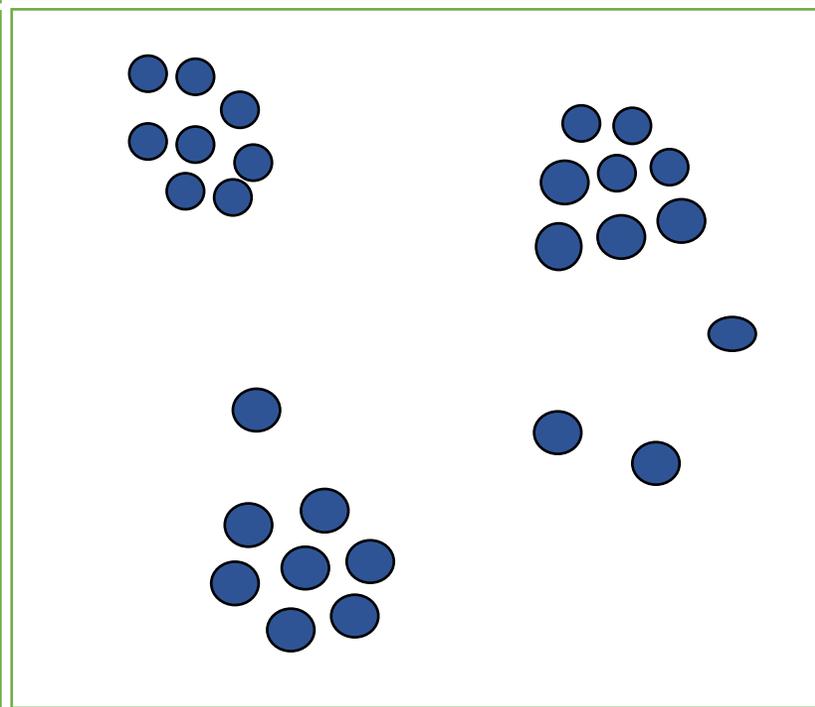
B



C



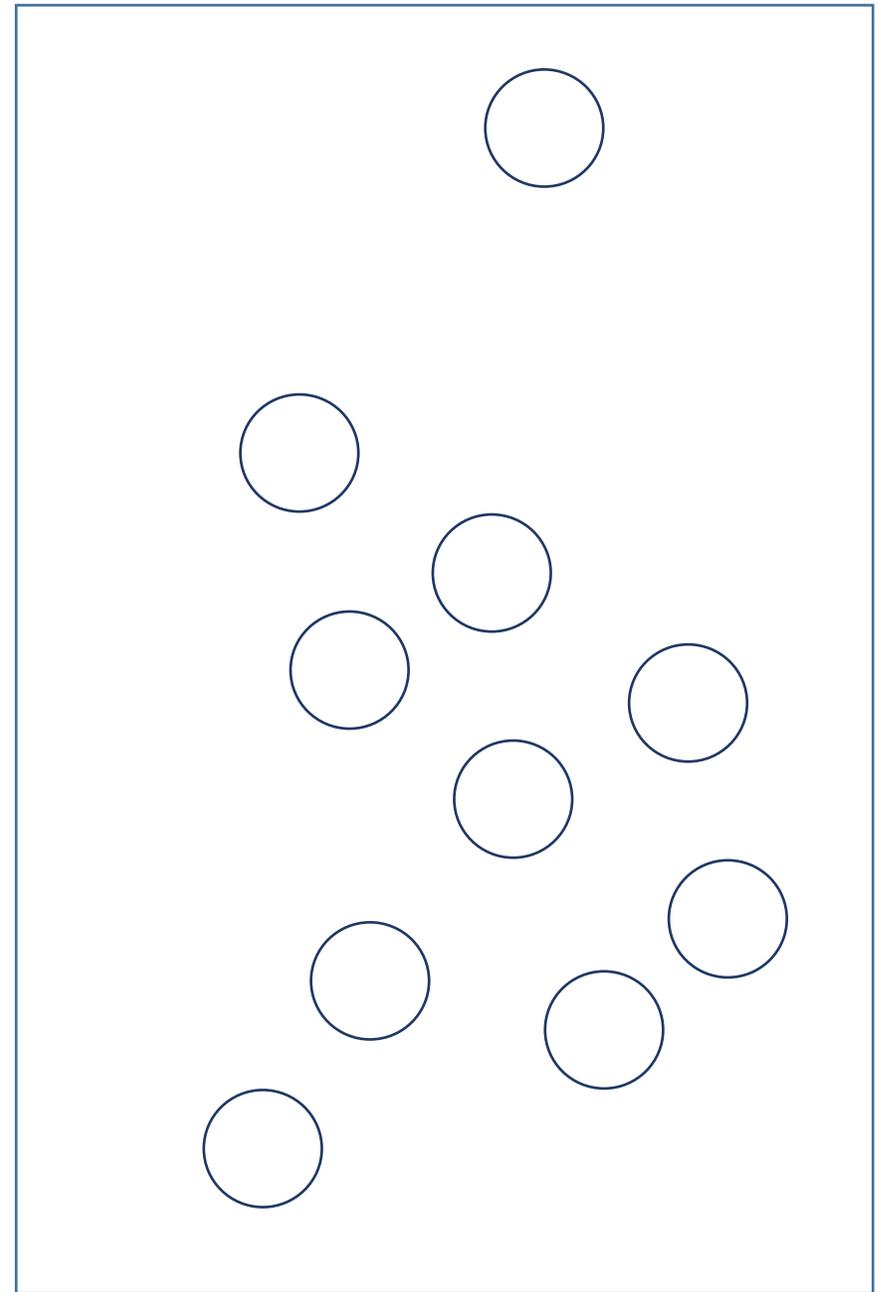
D

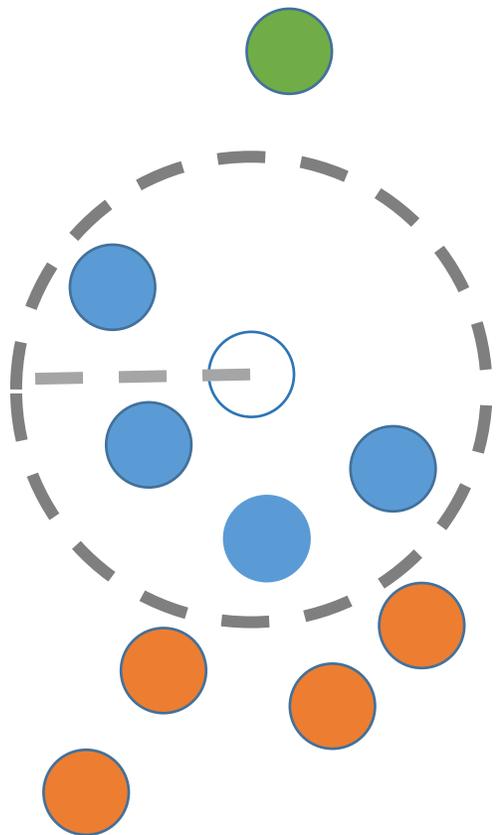


Для кластеризации
необходимы:

1. Расстояние
2. Центроиды

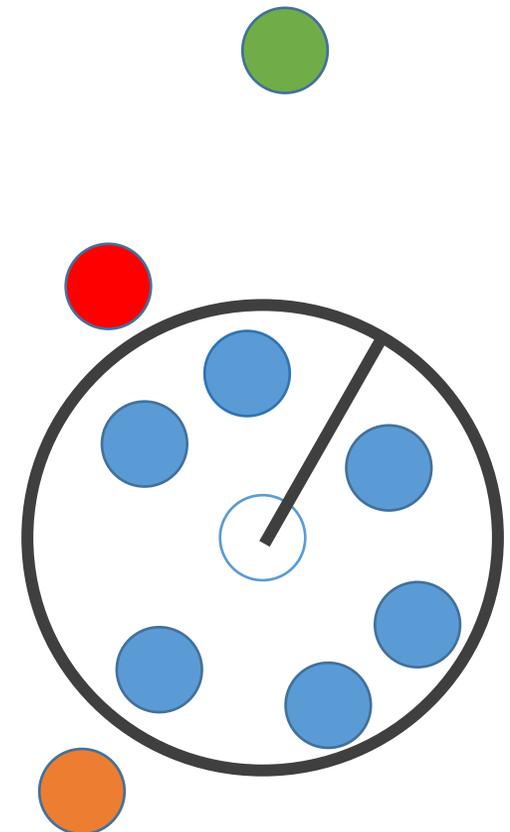
Цель – найти оптимальные
центроиды при данном
расстоянии



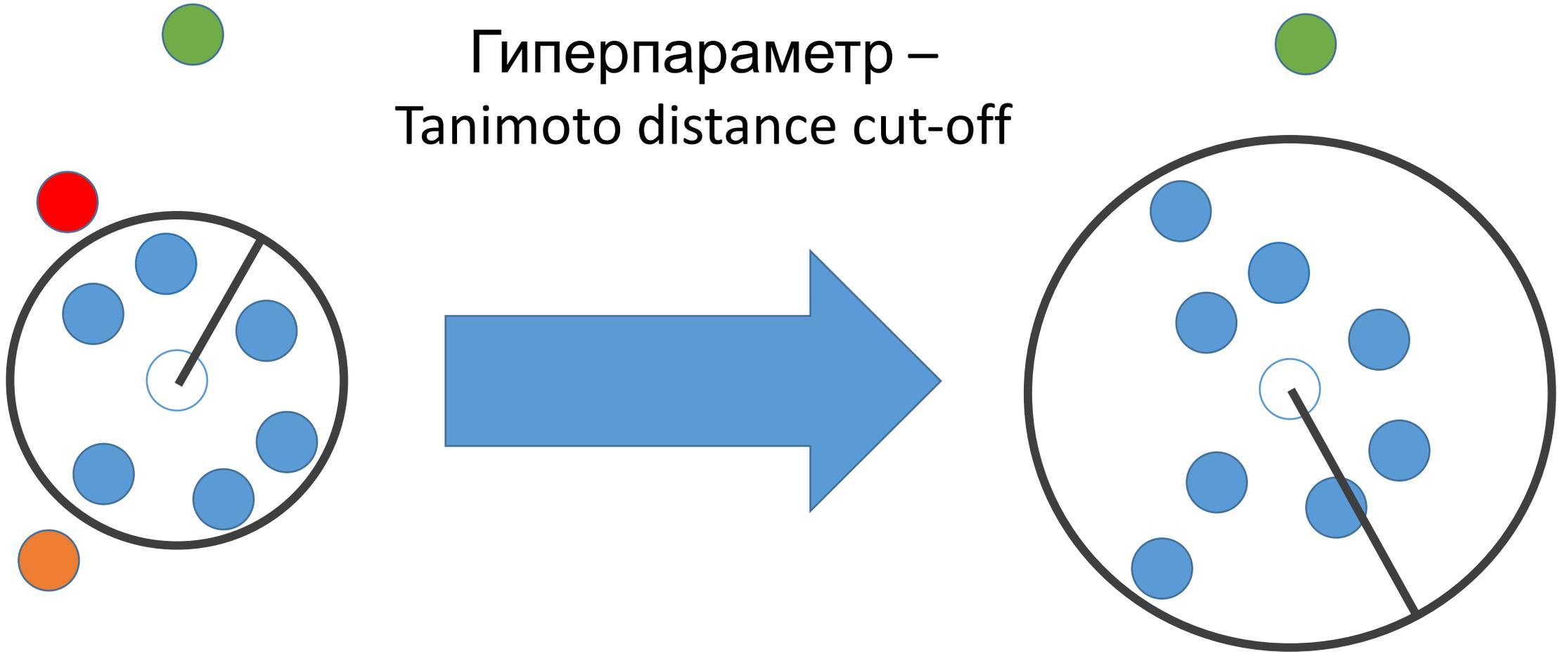


Не
оптимальный
центроид

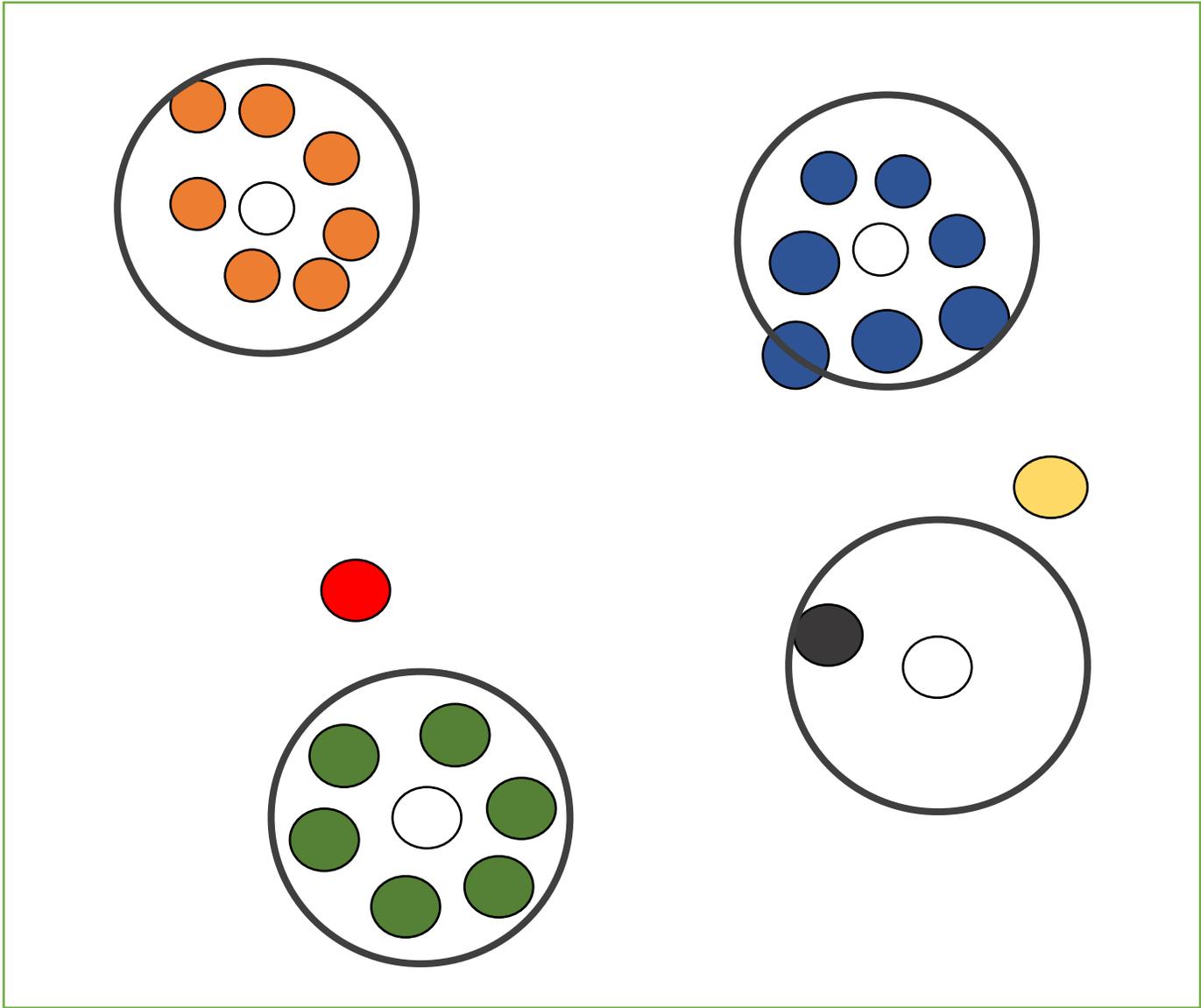
Оптимальны
й
центроид



Гиперпараметр – Tanimoto distance cut-off



Чем больше значение расстояния –
тем больше кластеры содержат элементов.
Тем меньше кластеров



```
def cluster_fingerprints(fingerprints, cutoff=0.2):
    tdm = tanimoto_distance_matrix(fingerprints)
    clusters = Butina.ClusterData(tdm, len(fingerprints), cutoff, isDistData=True)
    clusters = sorted(clusters, key=len, reverse=True)
    return clusters
```

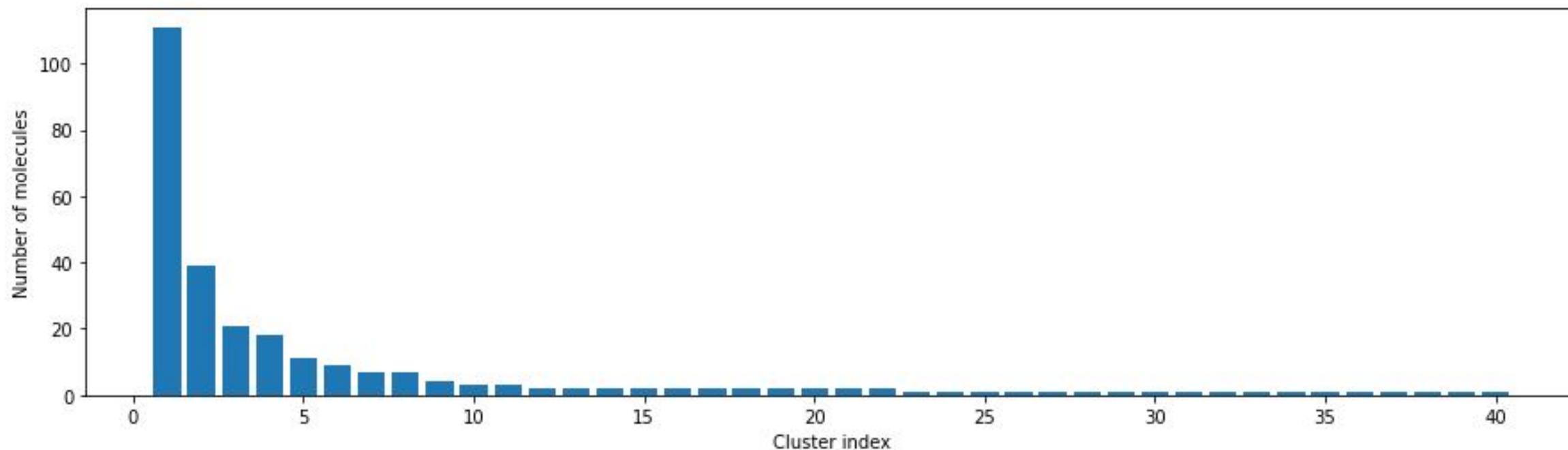
```
clusters = cluster_fingerprints(fingerprints, cutoff=0.35)
```

```
num_clust_g1 = sum(1 for c in clusters if len(c) == 1)
num_clust_g5 = sum(1 for c in clusters if len(c) > 5)
num_clust_g25 = sum(1 for c in clusters if len(c) > 25)
num_clust_g100 = sum(1 for c in clusters if len(c) > 100)
```

```
print("total # clusters: ", len(clusters))
print("# clusters with only 1 compound: ", num_clust_g1)
print("# clusters with >5 compounds: ", num_clust_g5)
print("# clusters with >25 compounds: ", num_clust_g25)
print("# clusters with >100 compounds: ", num_clust_g100)
```

```
total # clusters: 18
# clusters with only 1 compound: 6
# clusters with >5 compounds: 3
# clusters with >25 compounds: 2
# clusters with >100 compounds: 1
```

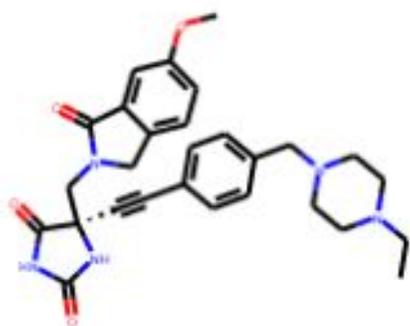
```
fig, ax = plt.subplots(figsize=(15, 4))
ax.set_xlabel("Cluster index")
ax.set_ylabel("Number of molecules")
ax.bar(range(1, len(clusters) + 1), [len(c) for c in clusters], lw=5);
```



Play with cut-off

```
print("Centroid molecules from first 7clusters:")  
# Draw molecules  
Draw.MolsToGridImage(  
    [compounds[clusters[i][0]][0] for i in range(7)],  
    legends=[compounds[clusters[i][0]][1] for i in range(7)],  
    molsPerRow=5,  
)
```

Centroid molecules from first 7clusters:



CHEMBL1287881



CHEMBL3947142



CHEMBL3640366



CHEMBL3642535



CHEMBL3642544



Спасибо за внимание