Anomaly detection on graphs

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joint work with P.-A. Noël, D. Vázquez, & P. Taslakian

- Problem
- Method
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Anomaly detection in graphs

We are trying to solve **unsupervised anomaly detection** on graphs:

- **Our input** is a graph where the nodes have a given set of features.
- **Our output** can either be a *binary labelling* or a *ranking* of the nodes.

The output should reflect some sense of **anomalousness** of the nodes.

Why is this problem interesting?

- Relates to **bot identification** in social networks.
- Can help improve **spam detection**.
- Relates to various types of **fraud**: *insurance*, *healthcare*, *financial*, etc.

➔ A good anomaly detection method could also help **other graph-based tasks**, such as *classification* or *clustering*.

Defining anomalies

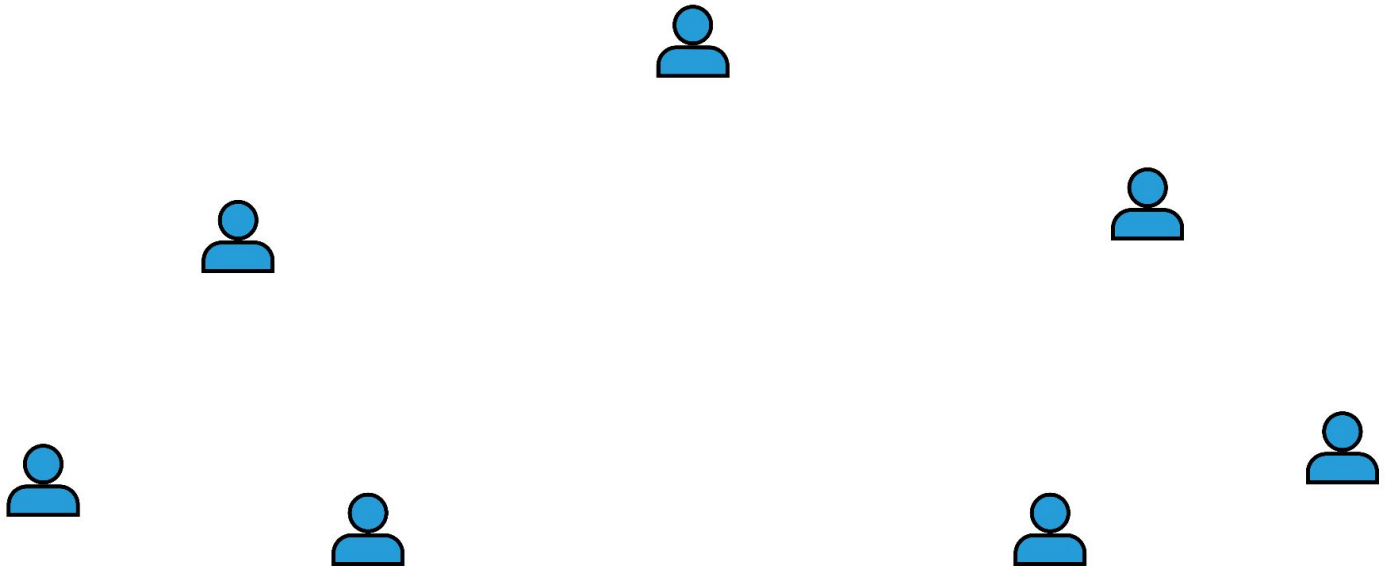
Defining anomalies on graphs is a **difficult task** since nodes have **two types of information**:

- *Personal information*, given by their **features**.
- *Community information*, given by their **neighbours**.

In that context, anomalies can have several forms:

- **Feature-based anomalies:** an anomaly can be defined uniquely *based on its features*.
- **Graph-based anomalies:** an anomaly can be defined uniquely *based on its neighbours* and the general graph structure.
- **Combined anomalies:** an anomaly can be defined not in the two previous ways, but by considering *both its features and the general graph structure*.

Defining anomalies (an example)



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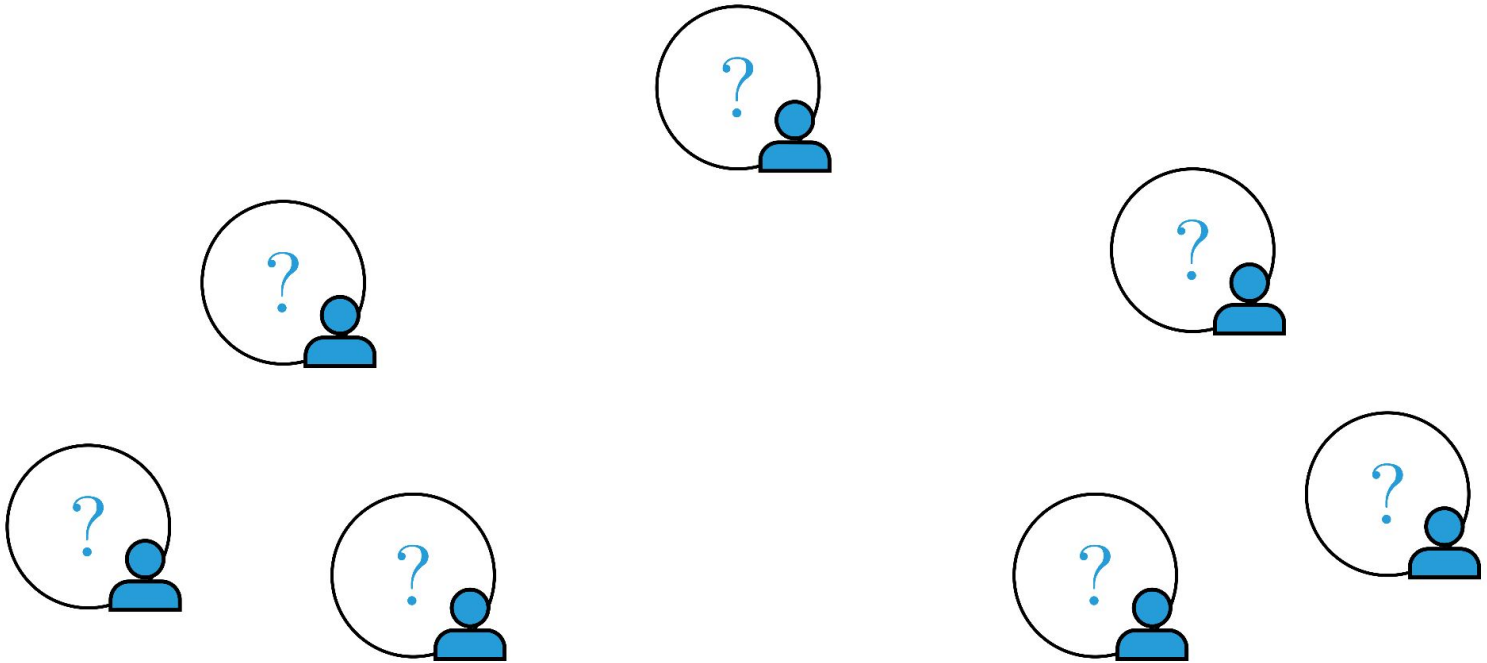

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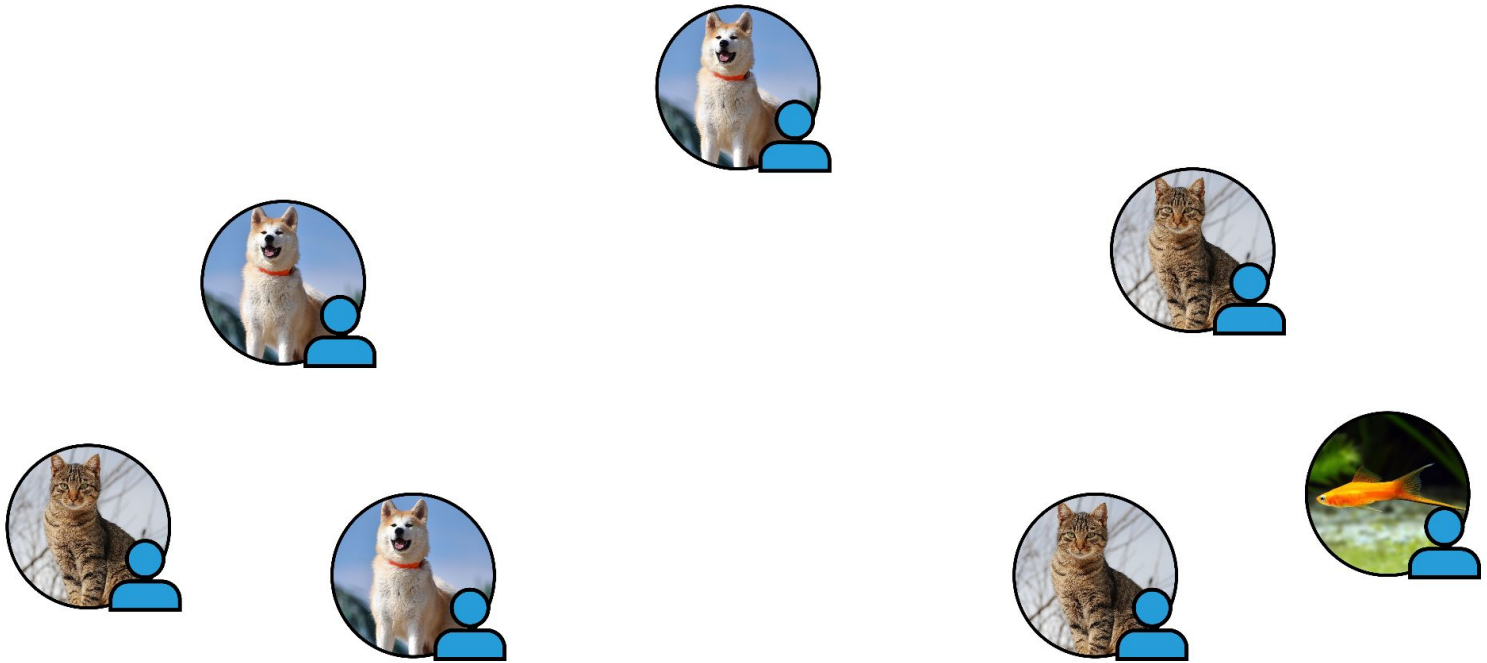

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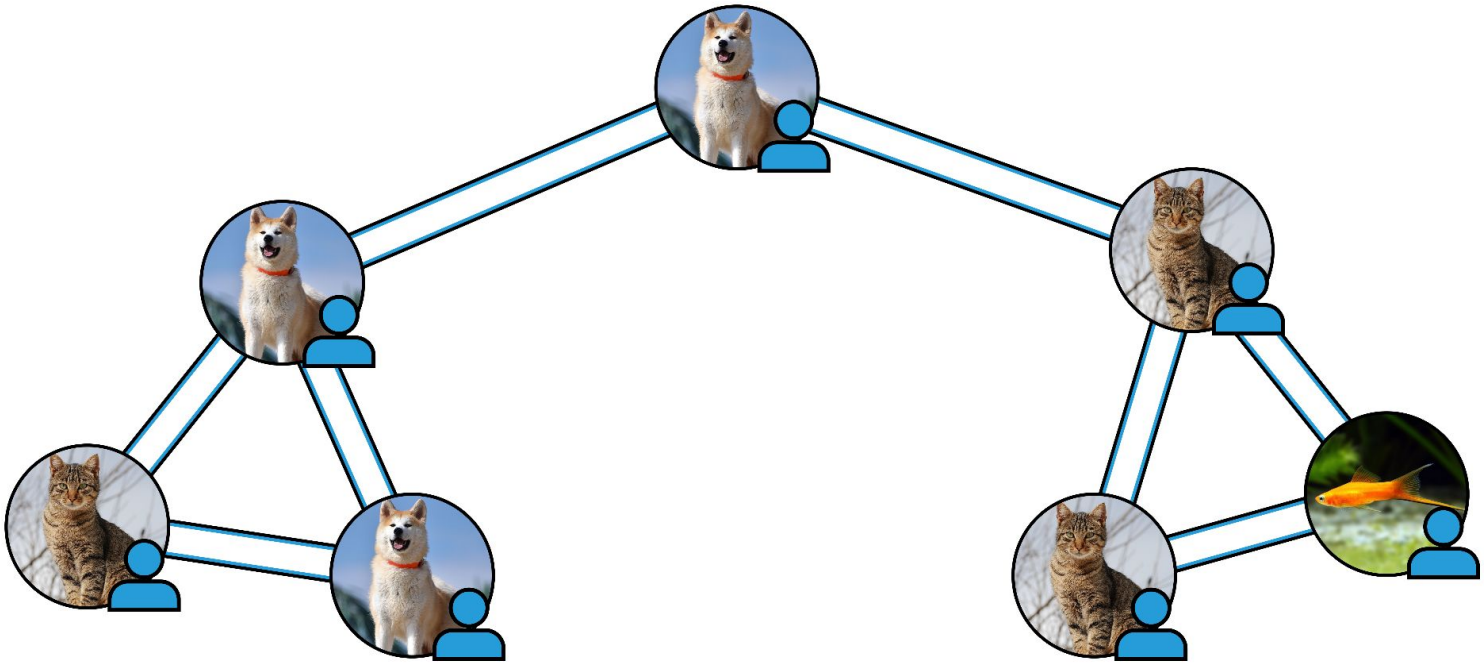

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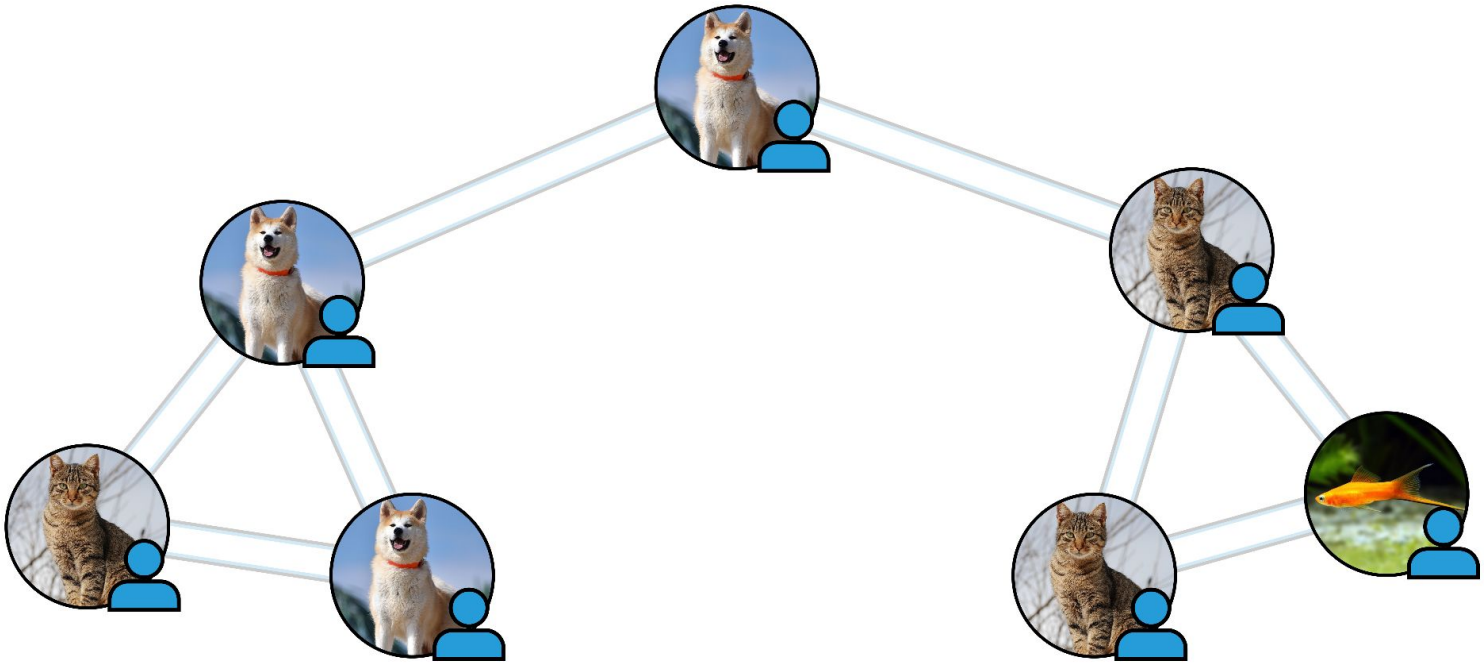

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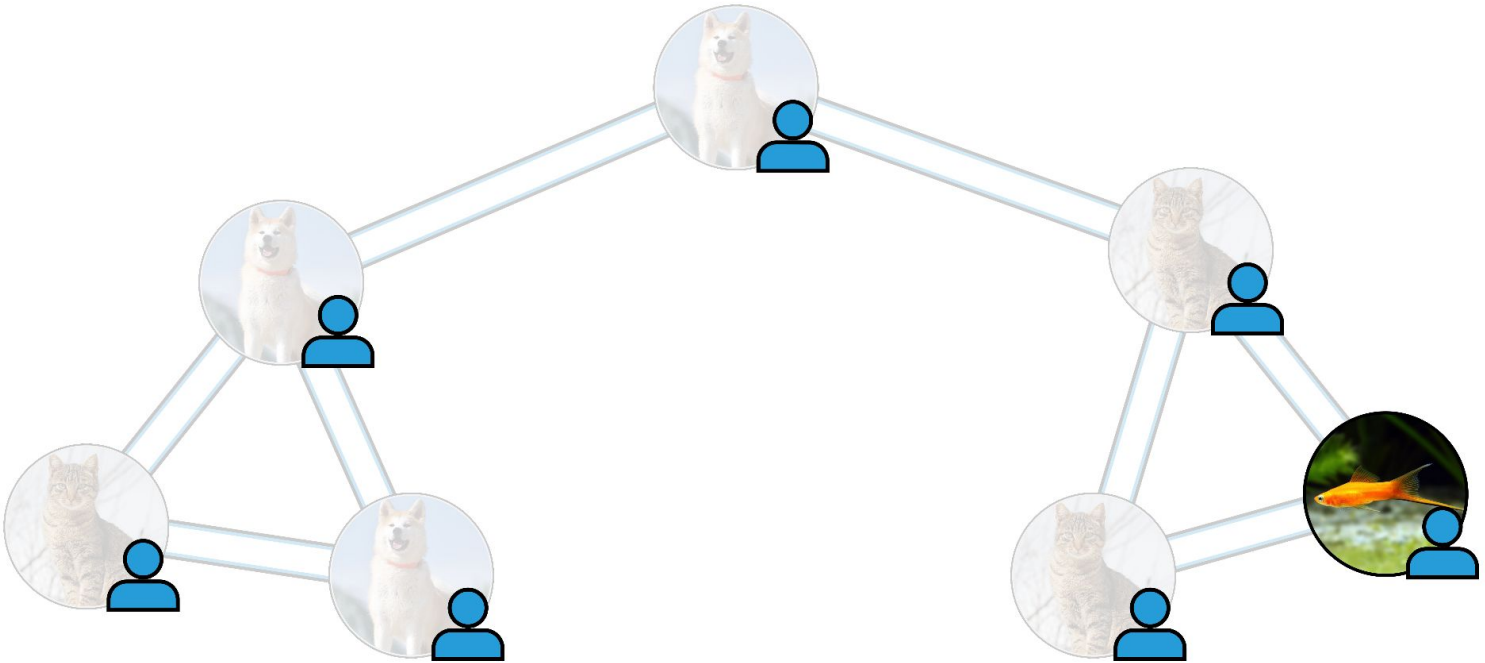

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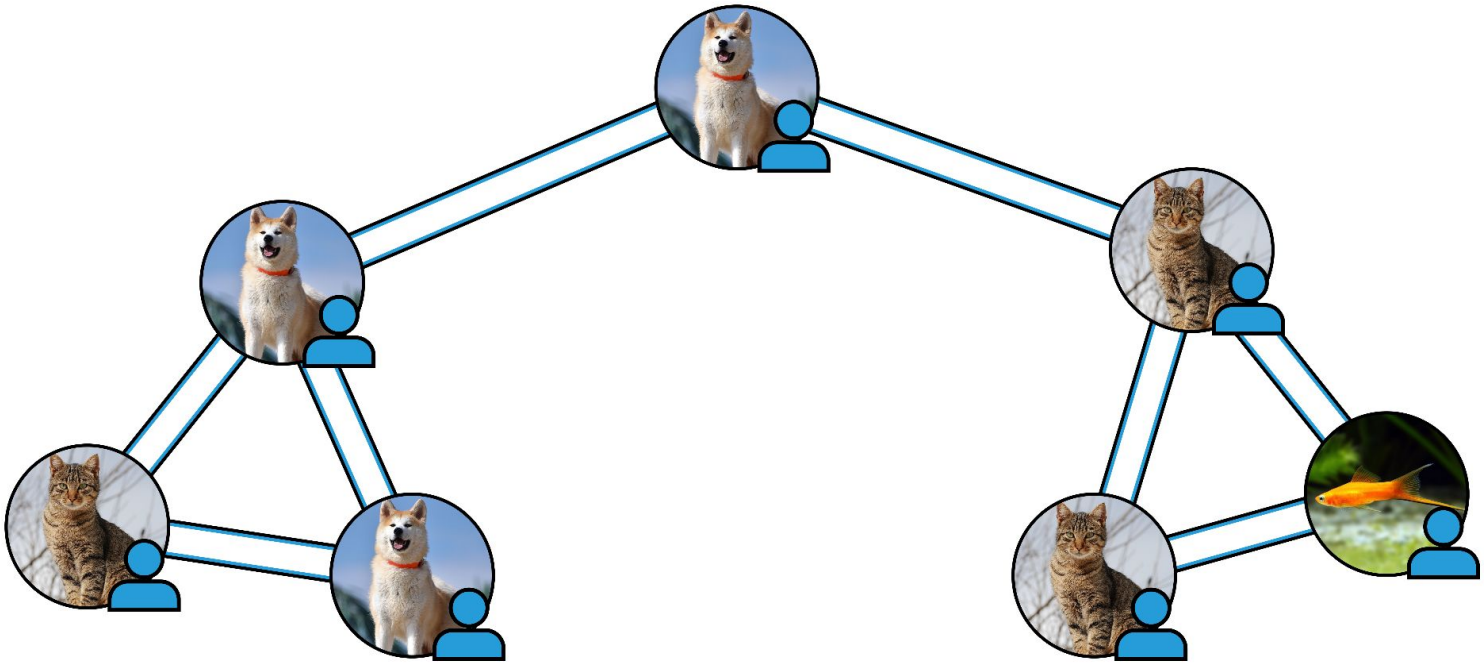

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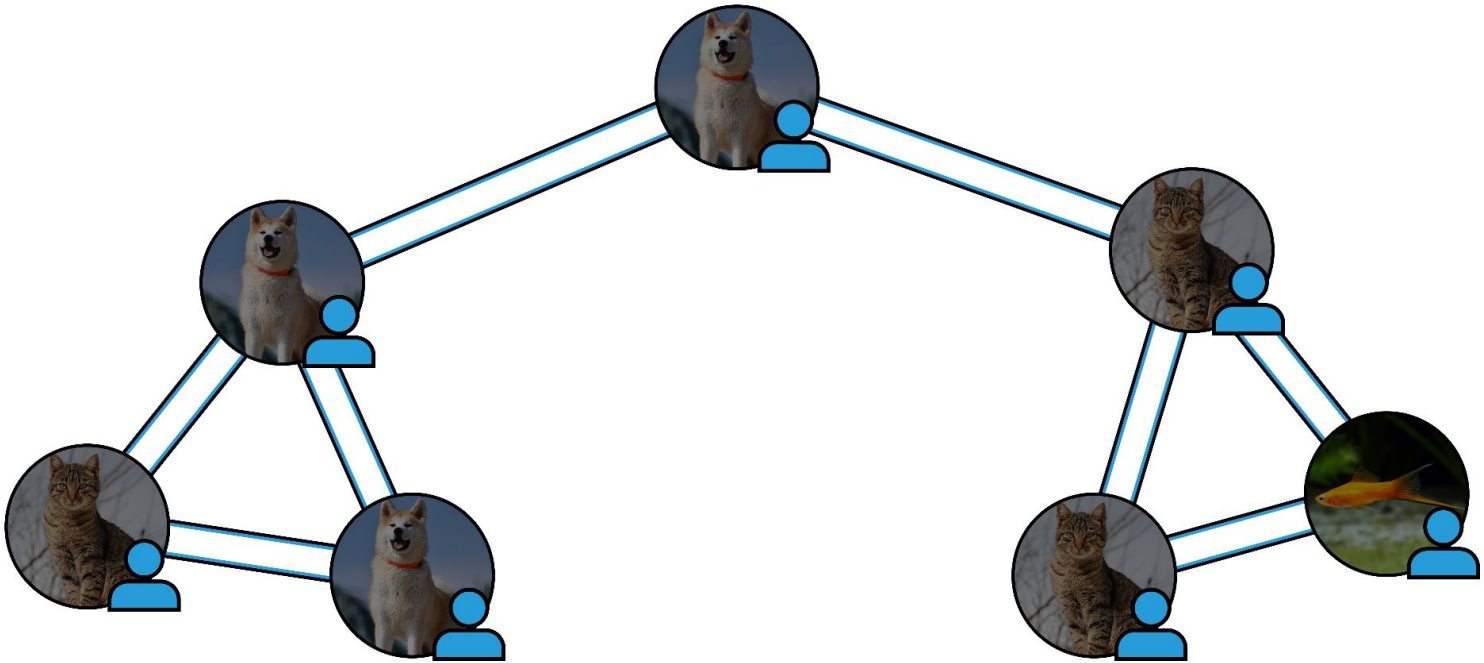

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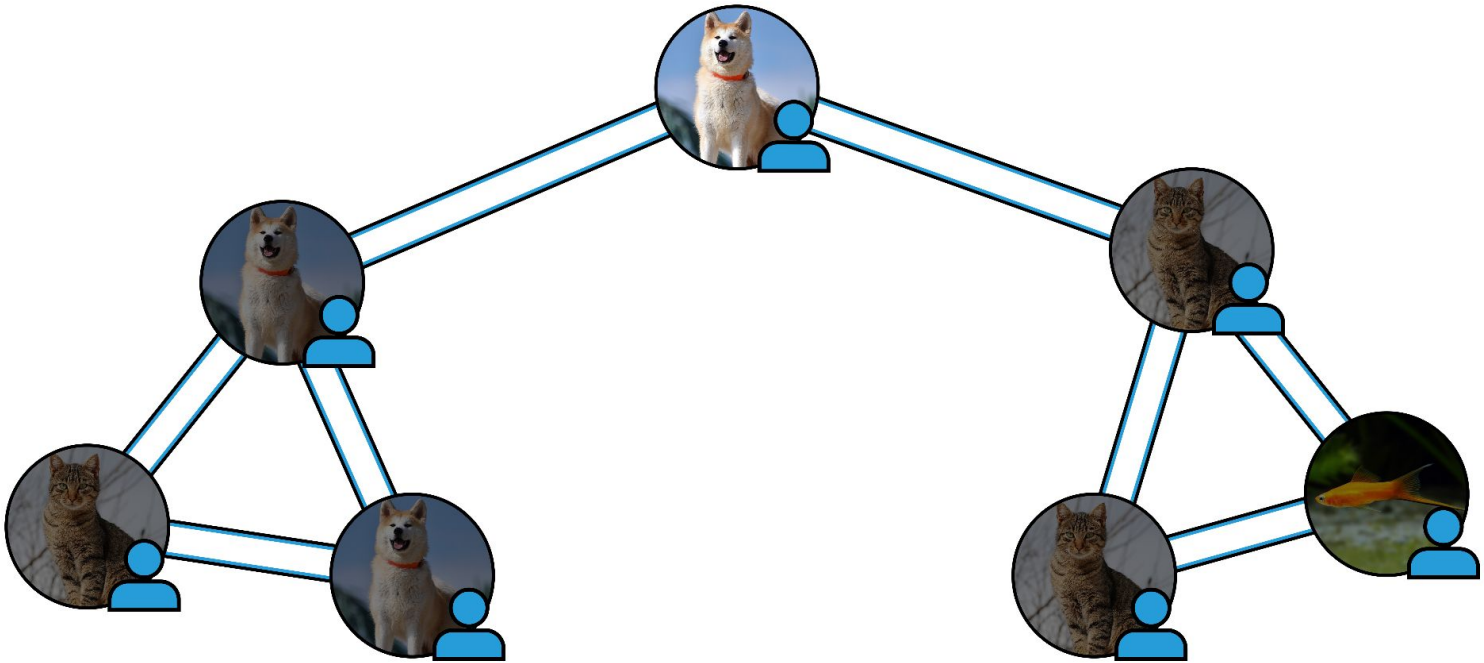

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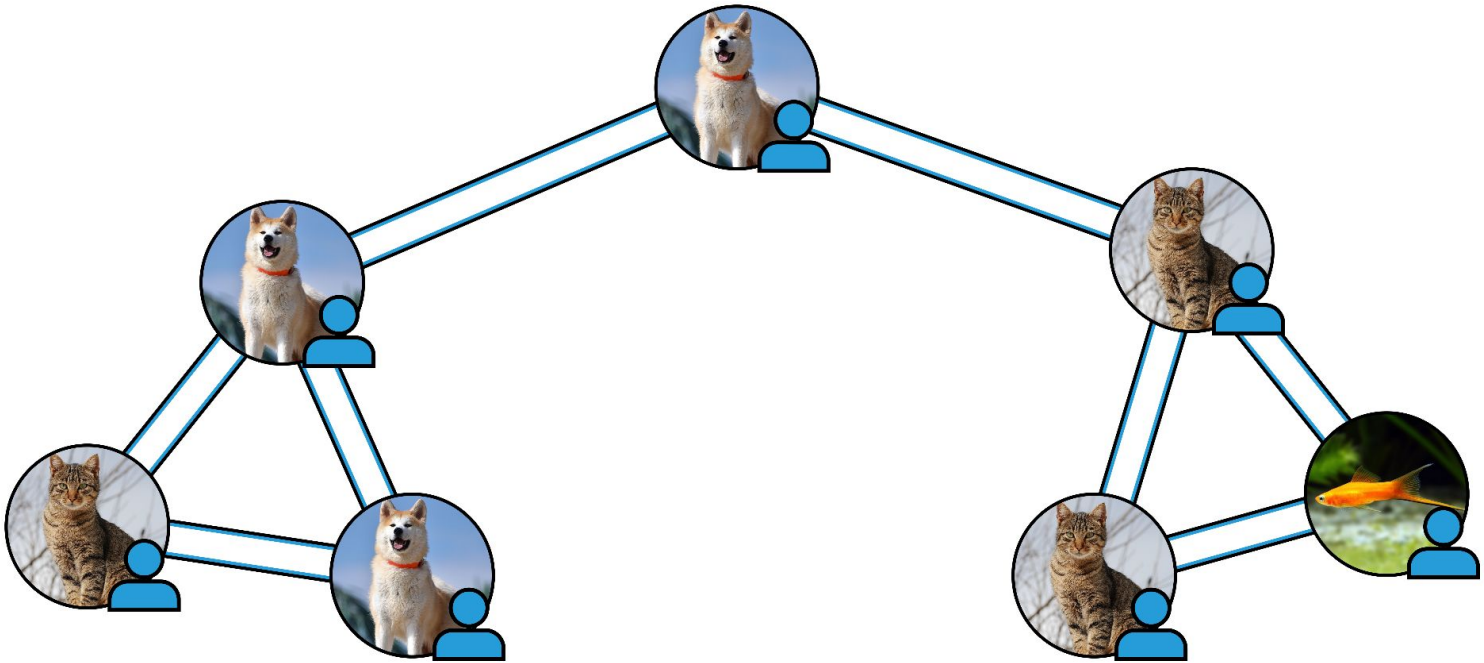

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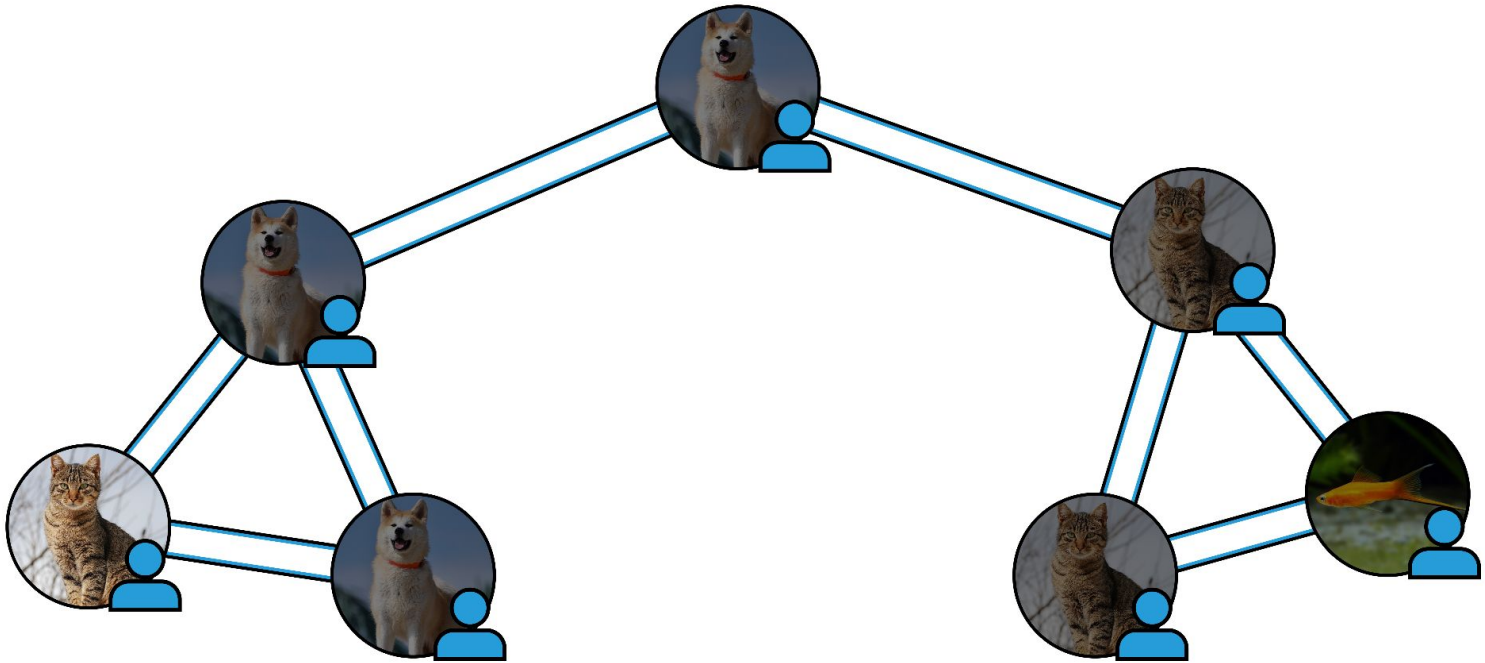

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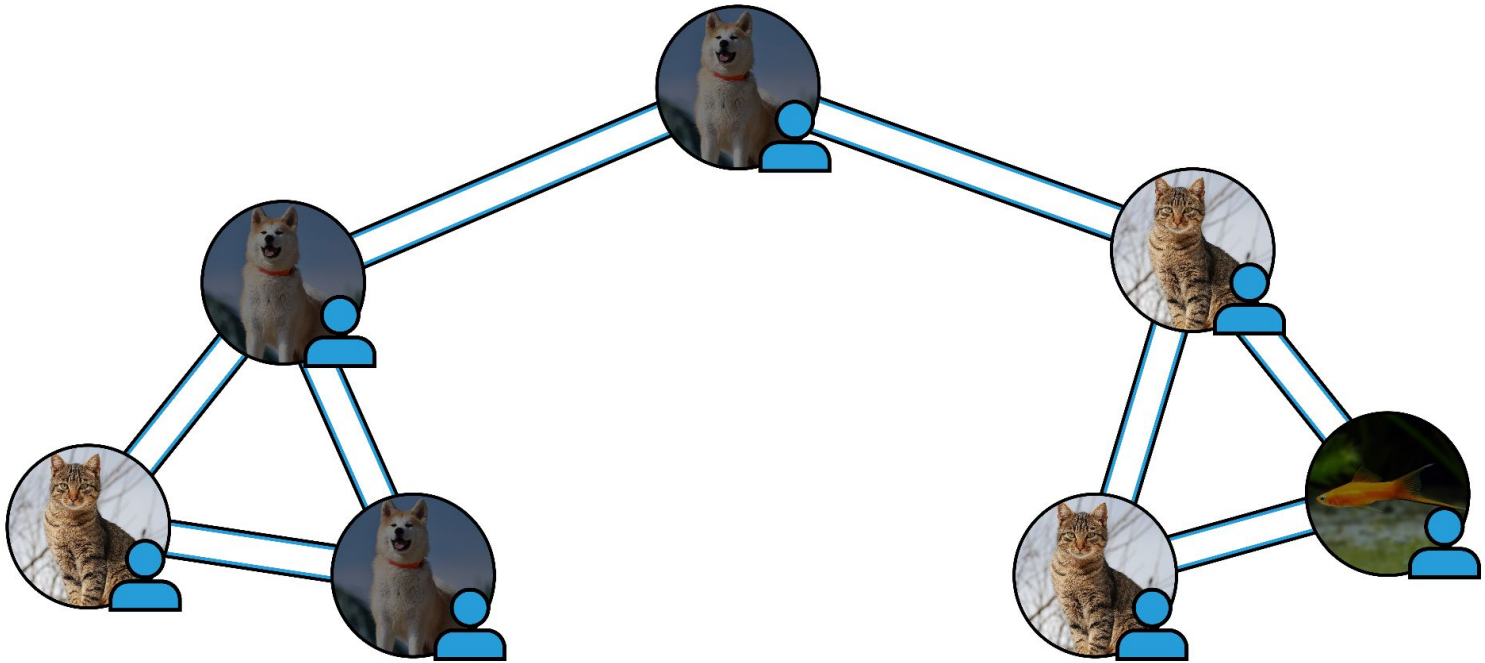

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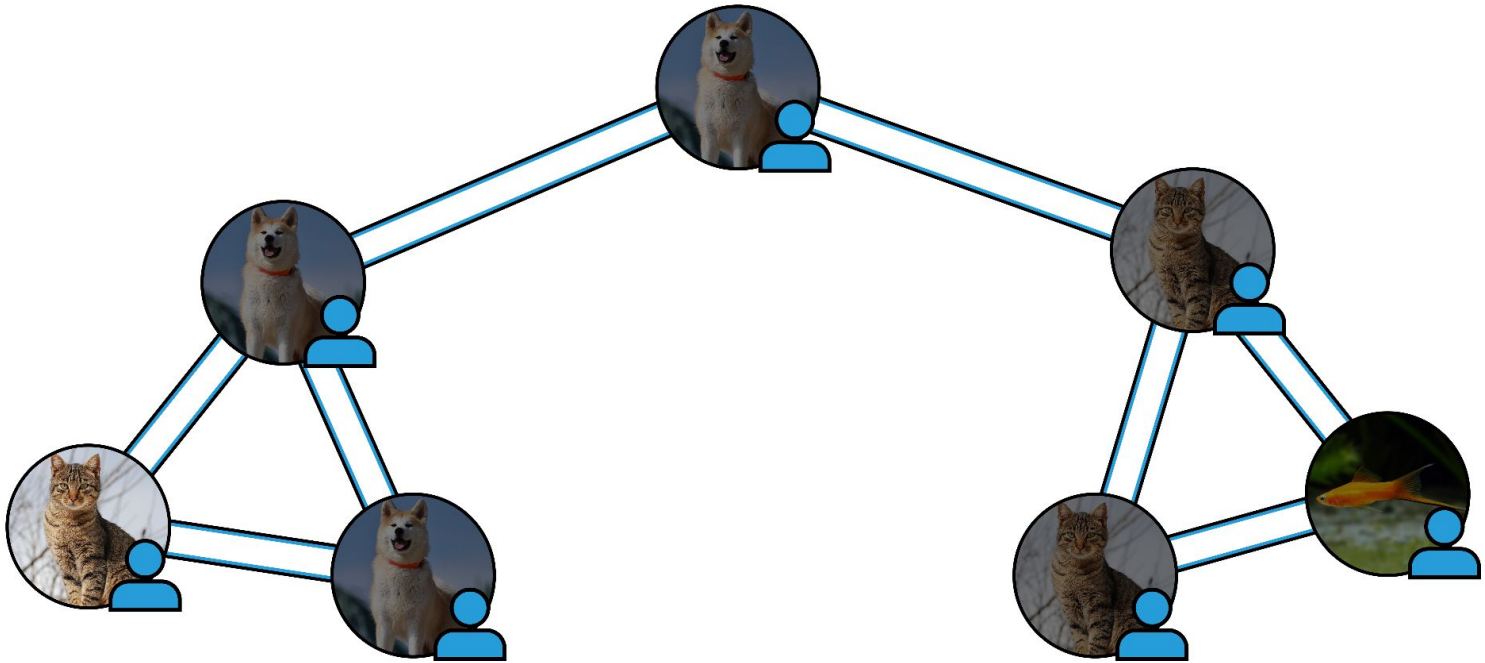

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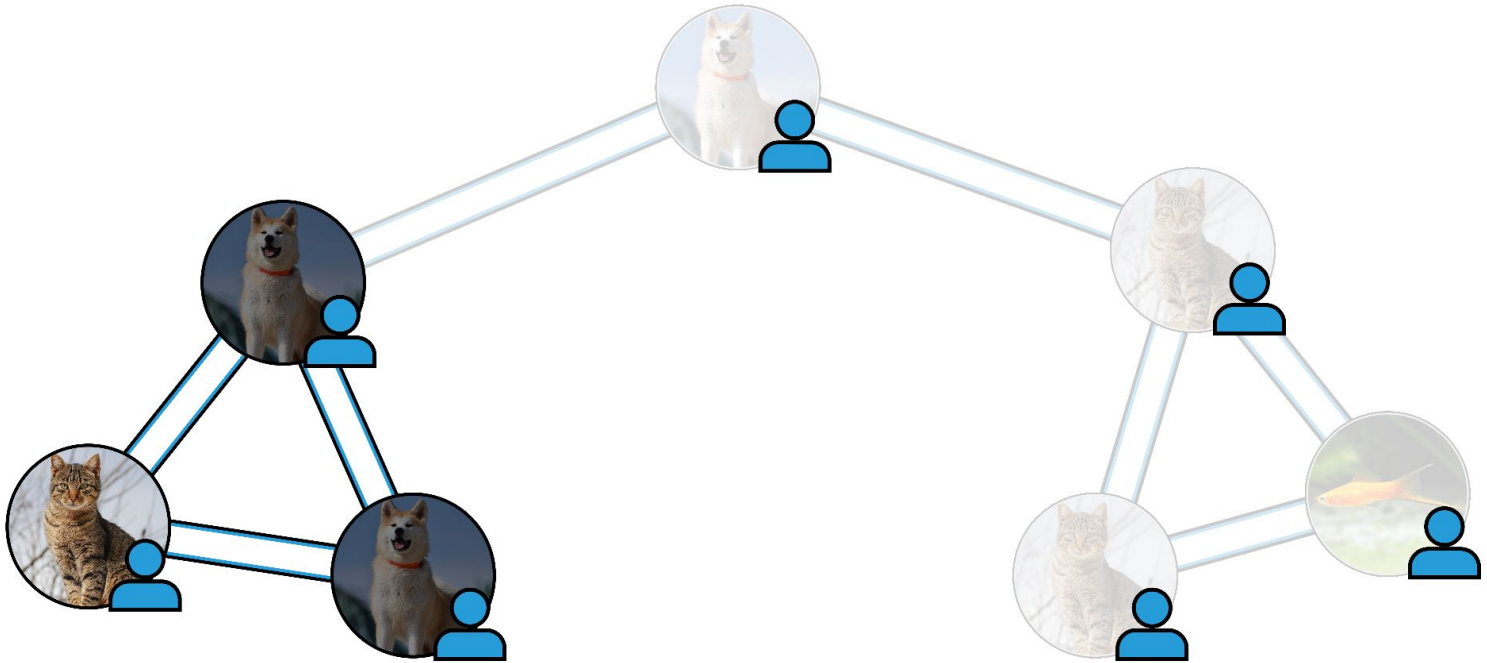

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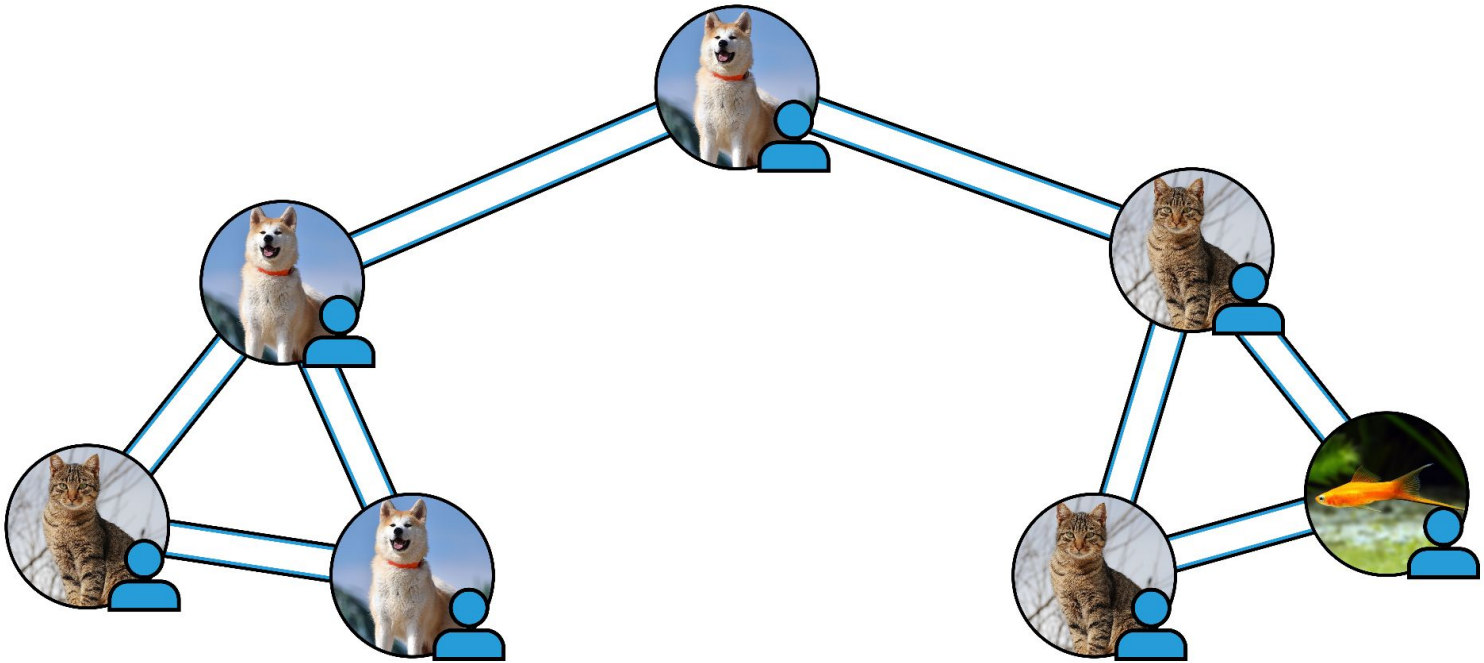

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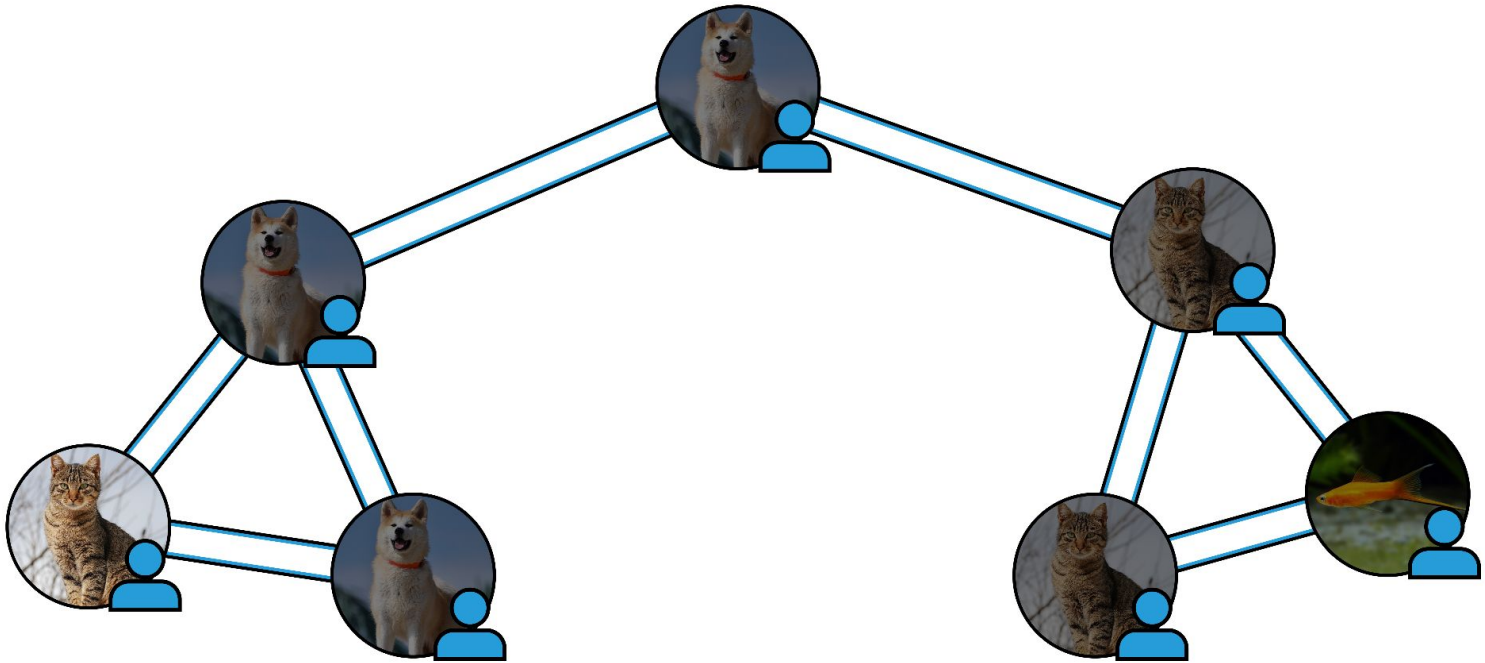

Previous work

The literature in anomaly detection on graphs is very **diverse** and **sparse**.

We did not find **direct baselines** and had to base our work on the following articles.

- **Multi-scale Anomaly Detection on Attribute Networks**, *L. Gutiérrez-Goméz, A. Bovet, J.-C. Delvenne*, 2019
- **Bayesian Robust Attributed Graph Clustering: Joint Learning of Partial Anomalies and Group Structure**, *A. Bojchevski, S. Günnemann*, 2018
- **Maximum Entropy Generators for Energy-Based Models**, *R. Kumar, S. Ozair, A. Goyal, A. Courville, Y. Bengio*, 2019

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General approach

Since we are using an **unsupervised method**, we do not have access to labels or examples of anomalies.

This is a realistic approach since:

- Anomalies are **rare**.
- Anomalies might be **very diverse**.

➔ The only assumption we can make is that **most nodes are normal**.

With these constraints, the **general approach** to anomaly detection is to:

- Define some **energy** of the nodes, related to their *likelihood of normality*.
- Use this energy to identify anomalies:
  - by **ranking** the nodes;
  - by considering the nodes with **highest energy**;
  - by identifying a **threshold** in the energy distribution.

Our method

The idea:

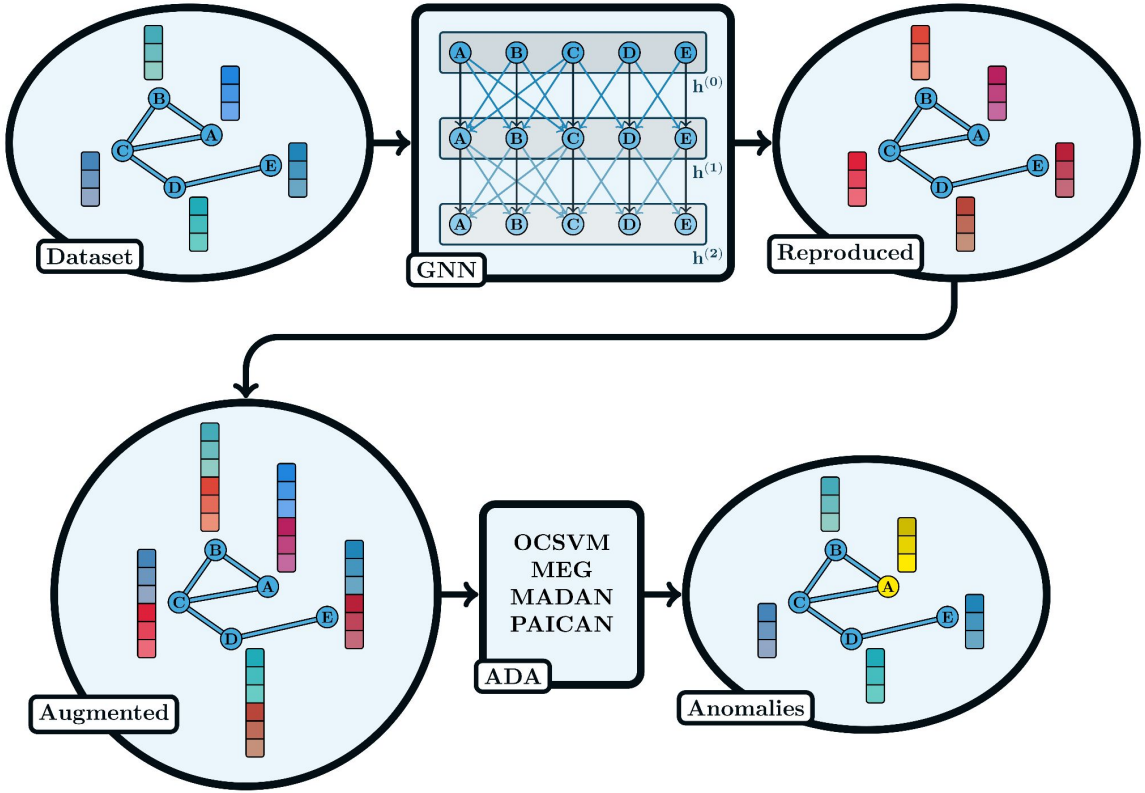
- We will **reproduce** the original features of the nodes with their expected values.
- We first **hide/mask** some of the features and then try to recreate them using the rest of the information.
- Use *Graph Neural Networks* (**GNNs**) for their high representative power.
- **Compare** the reproduced features with the original ones to identify anomalies.

➔ Creation of two algorithms: **HideGNN** and **MaskGNN**.

The general method:

- Take the graph as input, with node features.
- Use one of our two algorithms (**HideGNN** or **MaskGNN**) to reproduce the node features.
- Use these reproduced features to **augment the original dataset**.
- Apply an **anomaly detection algorithm** (ADA) on the augmented dataset.

Our method


Dataset
GNN
h(0)
h(1)
h(2)
Reproduced
Augmented
OCSVM
MEG
MADAN
PAICAN
ADA
Anomalies

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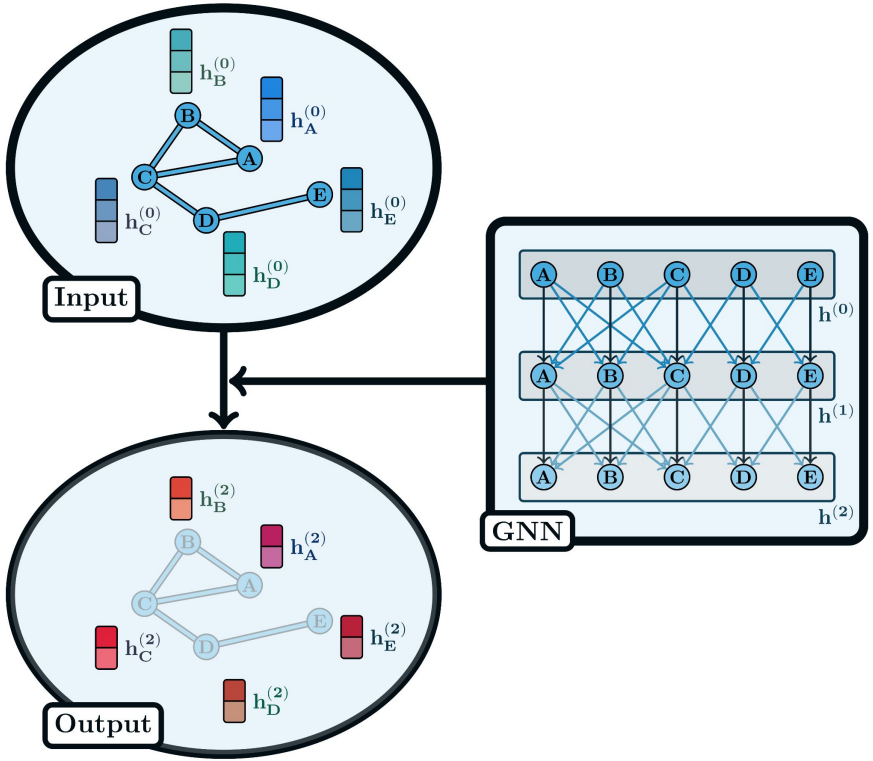
GNNs

GNNs are **commonly used** in machine learning methods on graphs.

They are based on a **message-passing** algorithm and have the advantage to:

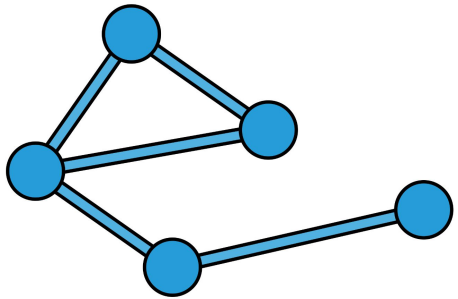
- use **both** the node features and the graph structure;
- and **not depend** on the ordering of the nodes.



HideGNN

The method:

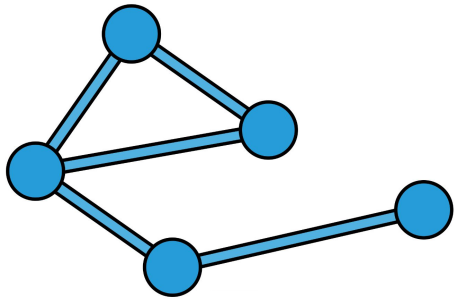
- Start by **hiding** a specific feature.
- Use a GNN on the **other features** to guess the hidden one.
- **Repeat** over all features.
- Eventually obtain **a set of GNNs** able to reproduce the original features.



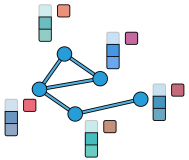
MaskGNN

The method:

- Start by creating a **random mask** over all features.
- **Replace** the masked features by some value (usually 0).
- Use a GNN to reproduce all features but **only optimize on the masked features**.
- **Resample** the random mask.
- Eventually obtain a **non-trivial GNN** which reproduces the original features.

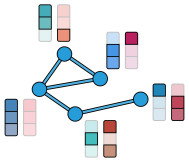


Pros and Cons



HideGNN

- **Pros:**
  - Complete reproduction of the features.
  - Less parameters.
- **Cons:**
  - Heavier to train.
  - Do not use any information from the hidden feature.



MaskGNN

- **Pros:**
  - Faster to train and using a single GNN.
  - Elegant all-in-one tool.
- **Cons:**
  - More parameters.
  - If not properly parametrized, likely to miss some information.
  - Less stable.

Remarks

On our algorithms:

- They are theoretically able to **overfit** and recreate the original features of the dataset.
- They learn from both the graph structure and the features, and their output contains a **lot of information** from the graph.
- They use a novel method combining GNN with methods from **NLP**, which opens the door to new parallel between the two fields.

On our method:

- It allows for **non graph-based algorithms** to be efficiently applied on graphs.
- It could easily be used on **other tasks**.

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Datasets

We tested our models on **three datasets**:

- **Disney:** 124 nodes and 6 anomalies.
- **Books:** 1418 nodes and 28 anomalies.
- **Enron:** 13533 nodes and 5 anomalies.

The inherent **extreme statistics** of these datasets makes this task complicated.

➔ Only Books allows an *acceptable* split into **train/valid/test**.

	Disney	Books	Enron
Nodes	124	1418	13533
Edges	335	3695	176987
Features	32	21	18
Outliers	6	28	5

Experimental setup

- Since only Books can be split, we use this dataset to **optimize** our algorithms.
- Once we finish running the algorithms, we use parameters with the best results on **valid of Books**.
- We then compute and **report** the results on the test set of Books and on Disney and Enron.

➔ We compare the ADAs **with or without** using our algorithms.

Some problems we encountered:

- None of these datasets were **already split** before our experiments.
- The results previously reported seem to be using the **test set** for hyperparameter tuning.
- We re-computed these results using our framework and found great **discrepancies**. We also did not always manage to recreate their experiments.
- These previous methods also seemed to be using a **modified version** of the datasets, with less features.

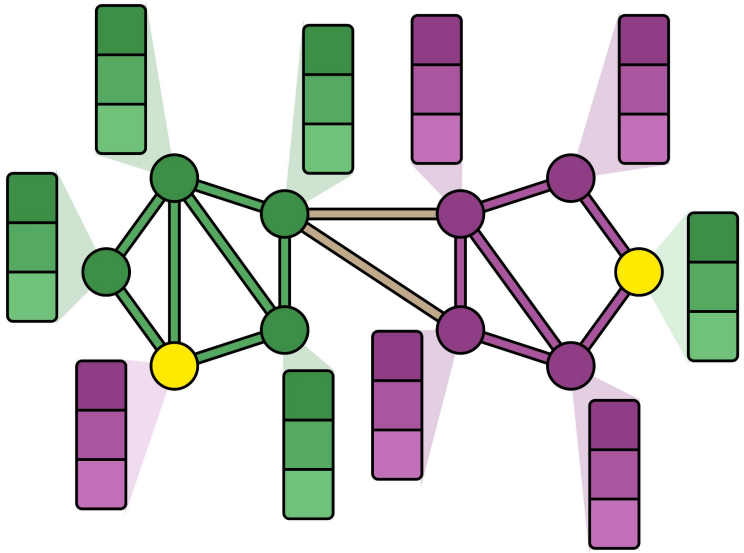
Our results

	Books		Disney*		Enron*	
	Original	Reduced	Original	Reduced	Original	Reduced
OCSVM†	35.90‡	37.33‡	36.44‡	**85.88**‡	55.90‡	43.22‡
Hide + OCSVM	49.58 (±1.47)	**52.21** (±2.41)	46.97 (±2.26)	43.16 (±1.03)	32.76 (±3.79)	**51.84** (±3.35)
Mask + OCSVM	**55.06** (±1.64)	48.49 (±2.07)	**47.63** (±1.73)	43.07 (±6.30)	**56.28** (±9.73)	50.46 (±6.55)
MEG† [24]	**63.12**‡	56.60‡	50.28‡	39.55‡	26.47‡	**63.08**‡
Hide + MEG	60.42 (±7.03)	**65.36** (±3.26)	46.51 (±6.51)	**69.44** (±3.47)	**44.22** (±14.05)	40.12 (±6.54)
Mask + MEG	57.06 (±6.55)	62.17 (±4.67)	**51.25** (±3.46)	62.44 (±13.38)	42.36 (±16.82)	40.63 (±12.21)
MADAN [13]	48.80‡	45.54‡	**67.51**‡	19.49‡	**61.81**‡	**73.64**‡
Hide + MADAN	**57.21** (±9.26)	52.08 (±7.64)	59.09 (±15.03)	**49.82** (±15.02)	54.24 (±14.41)	47.47 (±13.33)
Mask + MADAN	58.43 (±8.87)	**52.34** (±7.89)	55.98 (±14.07)	48.87 (±12.54)	60.55 (±14.58)	50.20 (±14.13)
PAICAN [2]	67.76‡	55.38‡	**75.14**‡	**73.45**‡	26.94‡	57.77‡
Hide + PAICAN	68.23 (±1.45)	**72.82** (±3.38)	62.73 (±8.14)	71.92 (±1.15)	**54.59** (±3.31)	58.65 (±10.07)
Mask + PAICAN	**68.90** (±1.15)	61.25 (±3.43)	67.31 (±6.87)	64.76 (±10.82)	45.92 (±8.08)	**65.40** (±5.46)

A synthetic dataset (Thanksgiving)

To try and understand our algorithms and results better, we created a **synthetic dataset**:

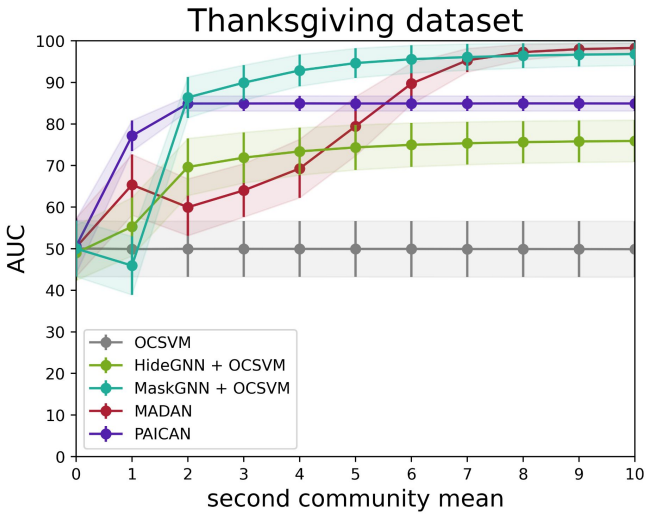
- Composed of **two communities**;
- Each community having a **given set of features**.
- We then modify the features of some members of one community to have the **features of the other community**.



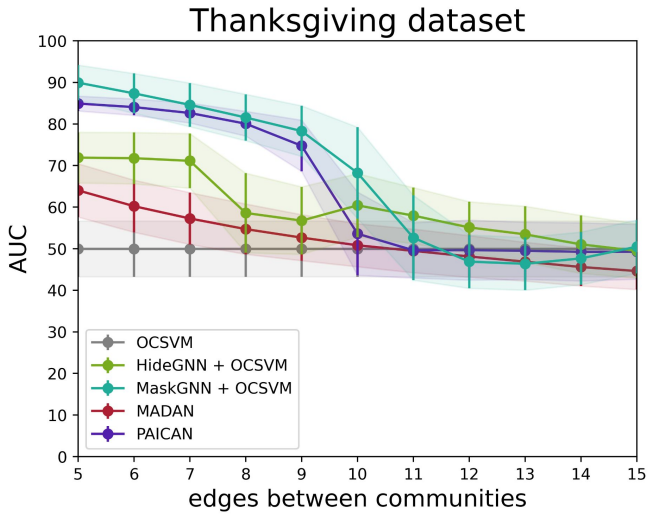
➔ This dataset only has **combined anomalies** and requires to use both the features and the graph structure.

Results on the synthetic dataset

Modifying the difference of **mean** between the two community features:



Modifying the **number of connections** between the two groups:



Thank you!