Anomaly detection for the Fink broker

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Plan

1. Introduction
    - What is Fink ?
    - Dataset
2. Goal and motivation
3. Graphs
    - Definition
    - Creation and performance
4. Anomalous and ambiguous data
5. Perspectives

Introduction

What is Fink ?

- Interface between telescopes and users

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- Interface between telescopes and users
- Community project since 2019
- $\sim$ 50 members in 13 countries

FINK

The data set

A dataset element (called an alert)

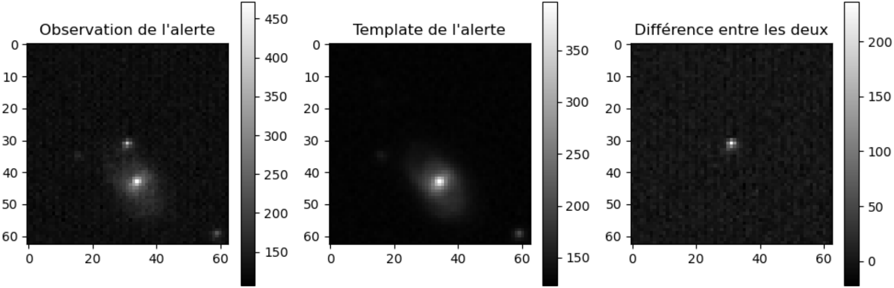
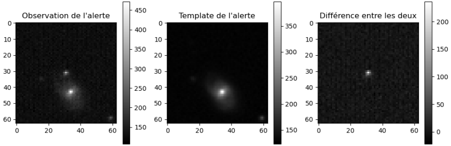


Figure 1: Issuing an alert

The data set

A dataset element (called an alert):

- 110 characteristics specific to alert observation

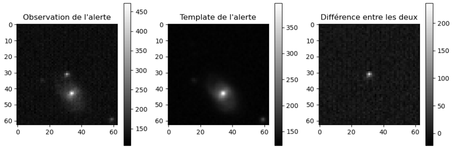


(a) Issuing an alert

The data set

A dataset element (called an alert):

- 110 characteristics specific to alert observation
- 80 statistical values calculated from the light curve



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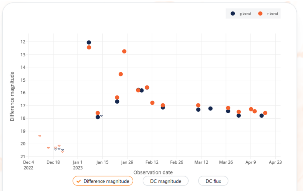

(b) Light curve of an object

The data set

A dataset element (called an alert):

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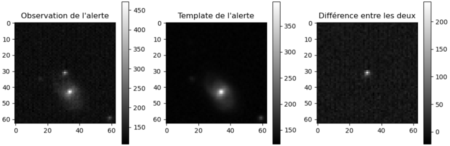
- 20 values added by Fink including a classification



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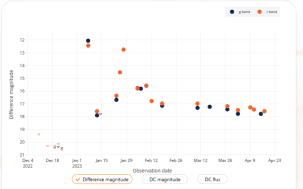

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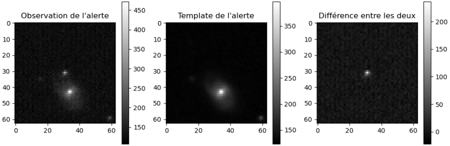

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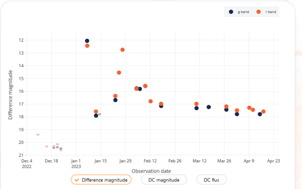

(b) Light curve of an object

Our dataset is composed of 6 distinct classes with 200 elements each

Goal and motivation

- Current situation: traditional tabular representation of alert properties

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- Identify anomalies among entities

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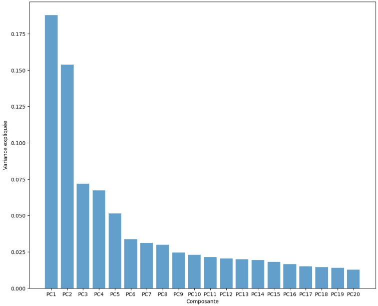

(a) Variance explained by principal component

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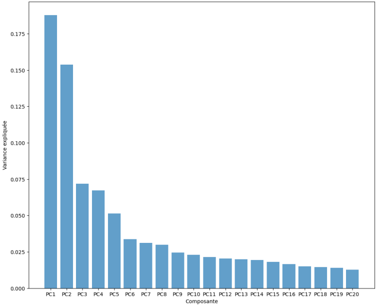

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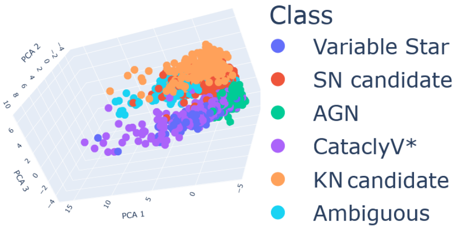

(b) Alerts based on the first three components

Graphs

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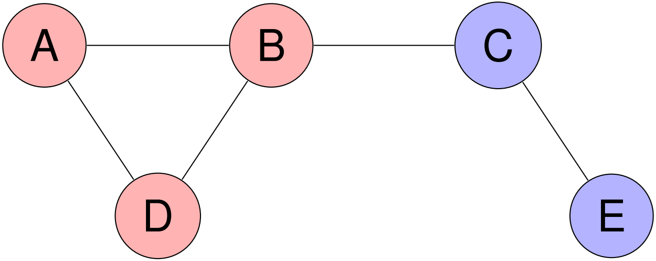

Figure 3: Example of a graph

In our case, vertex are alerts but how to define edges ?

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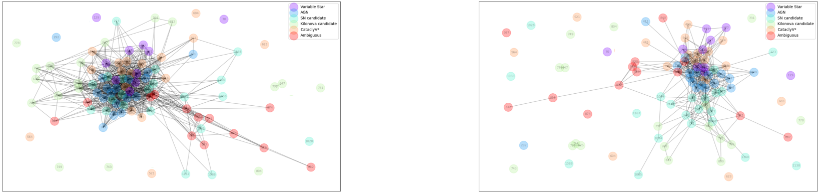

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(b) $n \log n$

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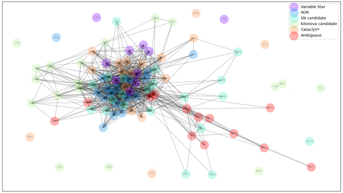

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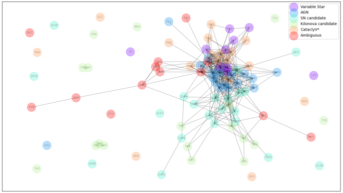
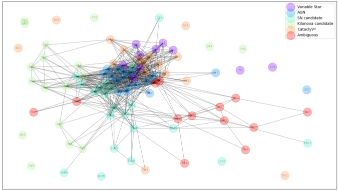


(b) $n\log n$



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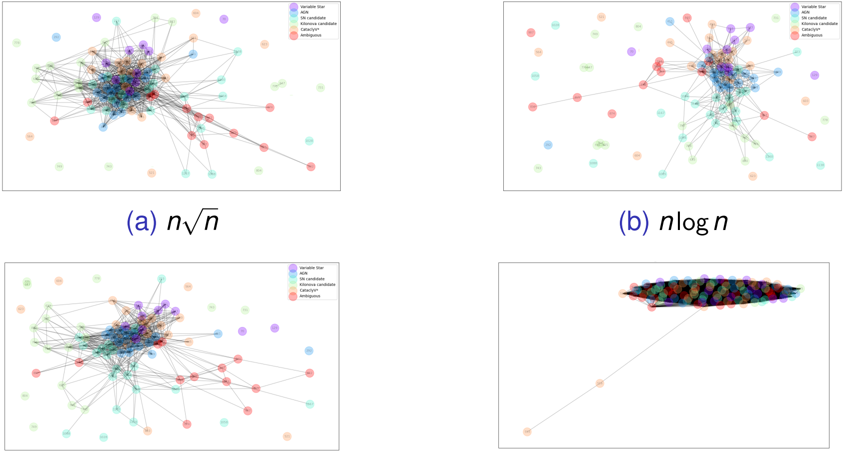

(a) $n\sqrt{n}$

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(c) Theorical number of edges

(d) One connected component

Performance measurement

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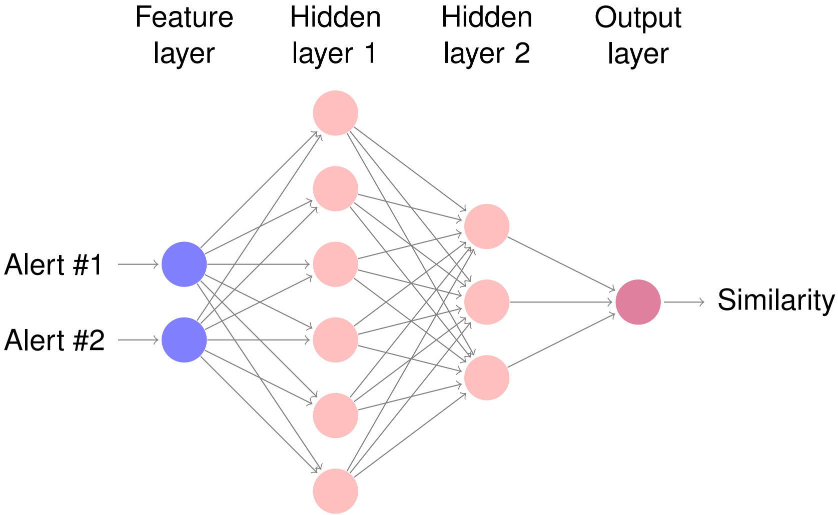
Type of construction	$n\sqrt{n}$	$n \log n$	TNE	OCC
Accuracy	34%	40%	36%	16%
Similarity density	38%	23%	34%	79%

Neural Network



Technical details: learning rate: 0.001, 200 epochs, Loss function: Binary Cross Entropy, optimizer: Adam
Framework used: Pytorch
Training set: 200 alerts, Test set: 200 alerts

Result

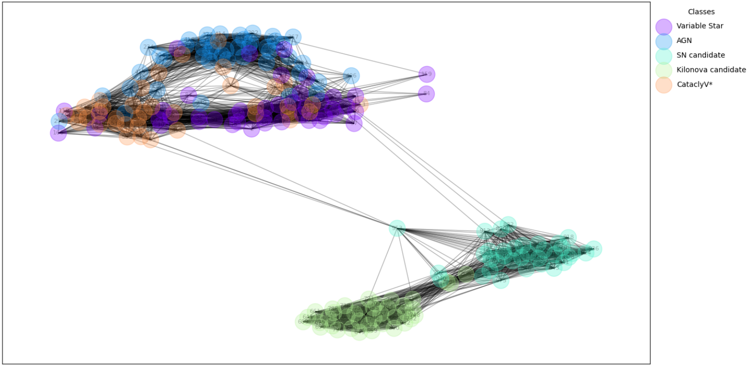


Figure 5: Neural network graph

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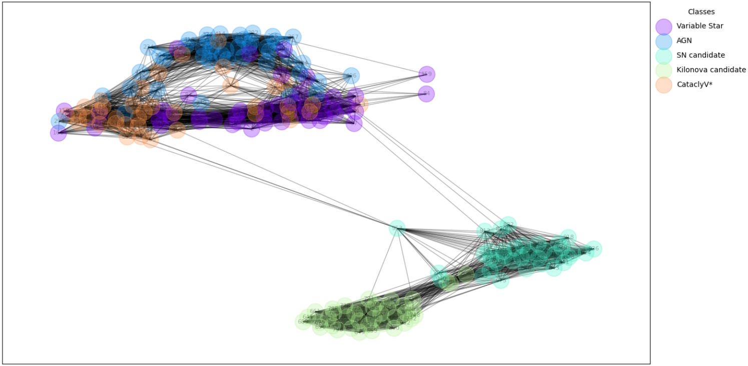

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Accuracy	Similarity density
64%	61%

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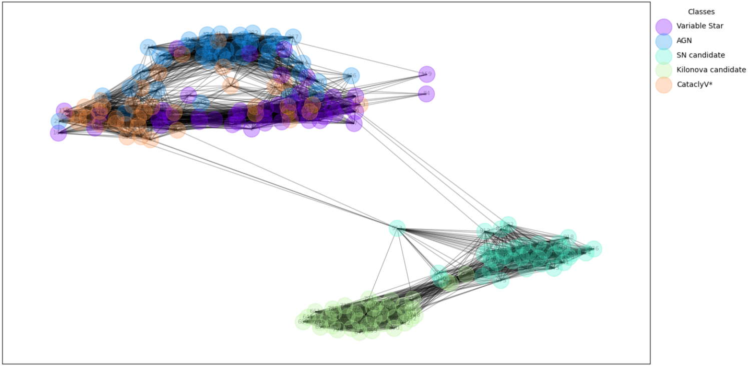

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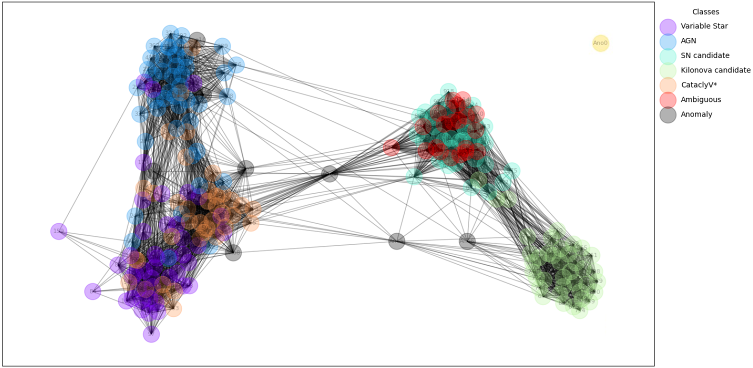
78% of alerts are linked to a majority of alerts of the same type

What about anomalies ?



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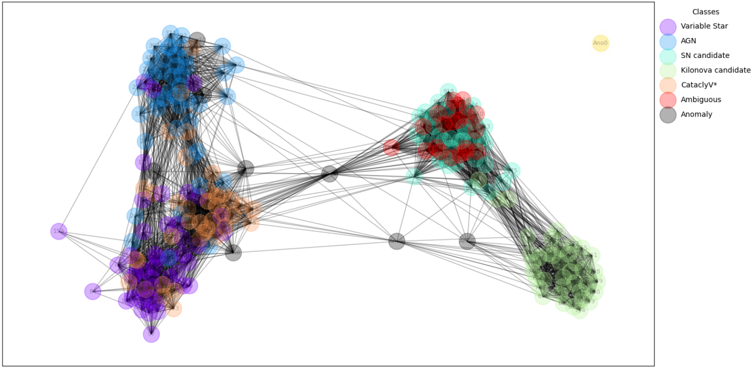

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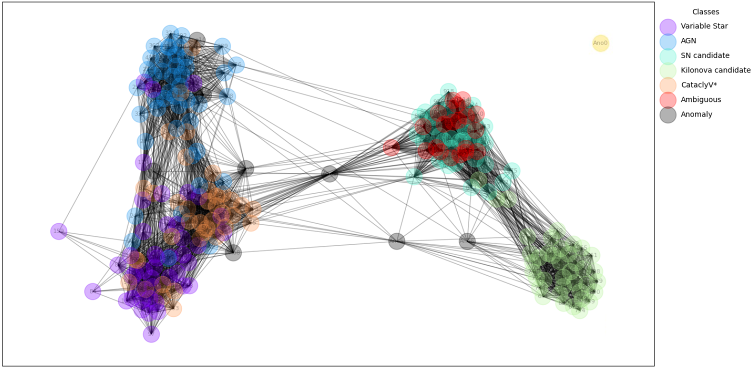

Figure 6: Adding anomalies and ambiguous alerts

- Anomalous alerts are connected in a particular way
- Ambiguous alerts are connected to an average of 90% of supernovas

Perspectives

Potential improvement

- Stabilize results: Impact of the training dataset
- Refine prediction: Graph neural network
- Scaling up: Hypergraphs
- Improving the interpretability of predictions: Modifying the loss function

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Short term application

- Recommendation system
- Detection of potential anomalies
- Enhance Fink services for the scientific community

Thank you for your attention
Any questions ?