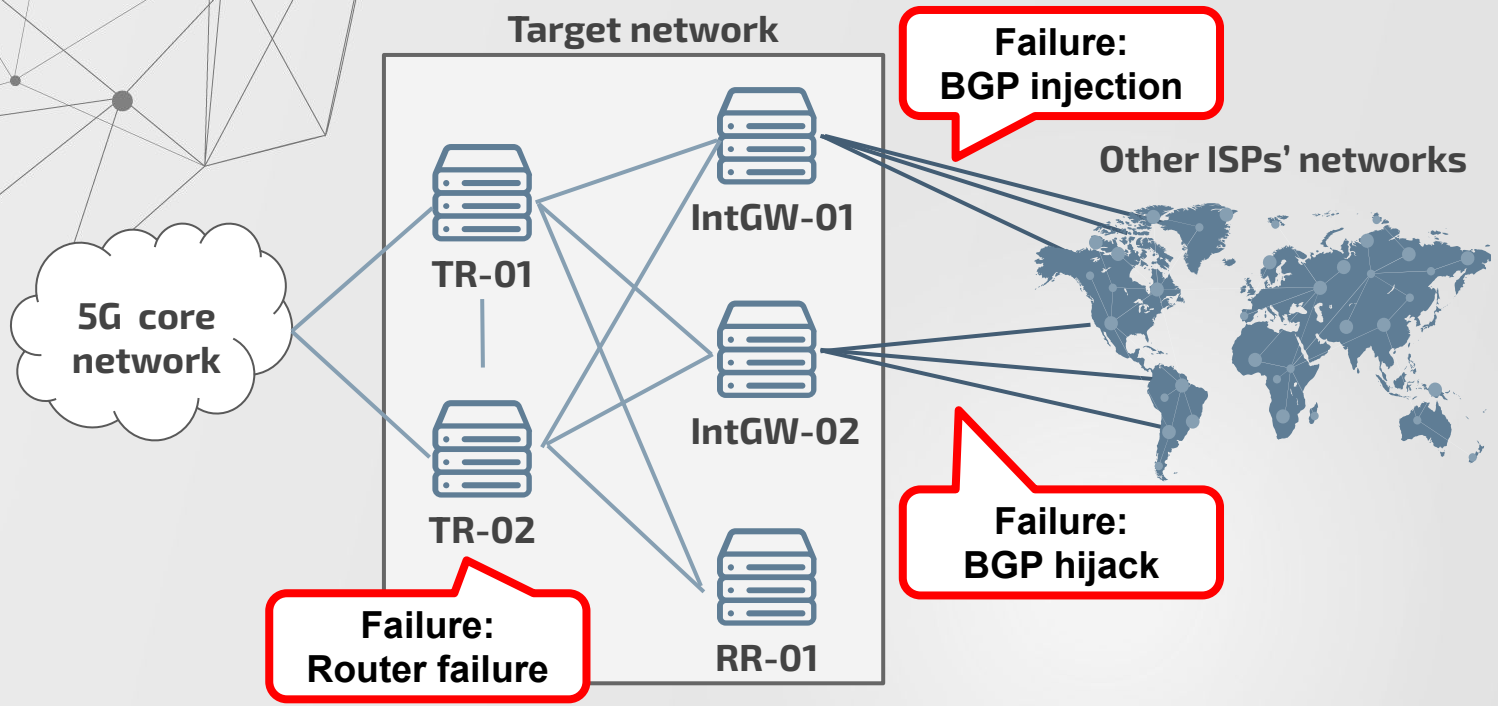
Pre-training and fine-tuning approach for detecting route information failures in IP core networks

team mlab 2020/12/15

Background — Difficulty of failure detection in BGP network

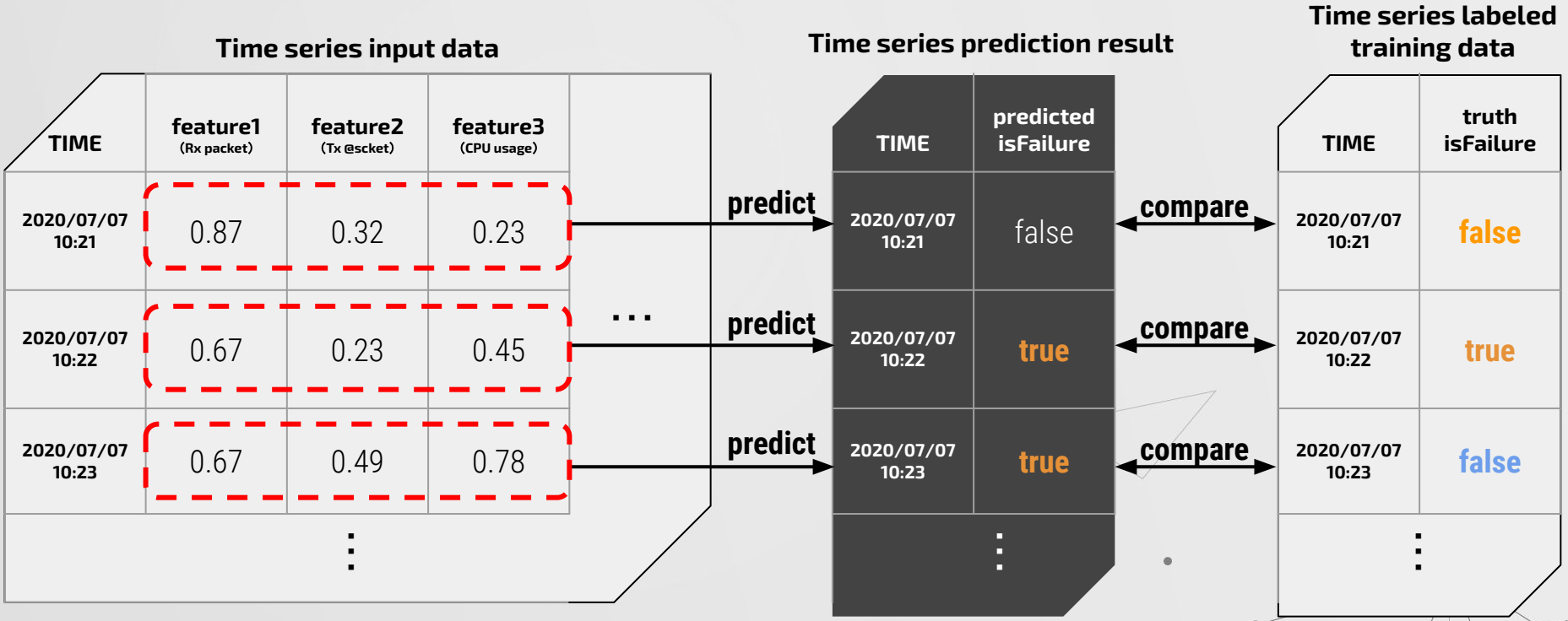


Difficulty

Conventional rule-based approach is NOT applicable because
BGP does not have a mechanism to authenticate each router configuration

Problem Description — Failure Detection in BGP Network

- Objective: Detect the failures in the BGP network from the network status information
- Input: Time series data obtained from the border gateway routers

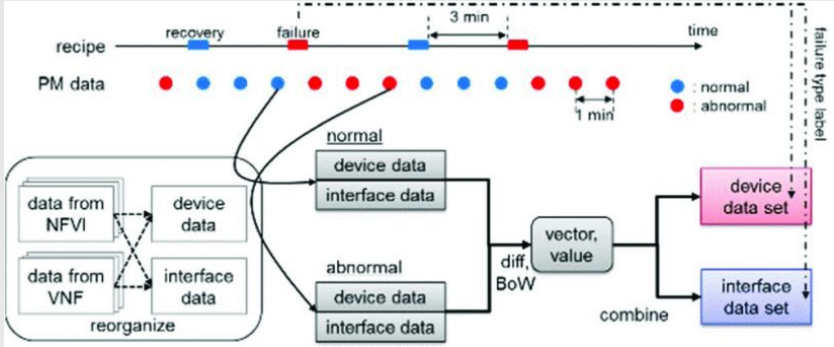


Related Work – Fault classification using machine learning in an NFV environment [Kawasaki+20]

Failure Scenario:
Node-down, Interface-down, and CPU overload

Preprocessor:
Bag-of-Words (Bow) using labeled training data

Fault Classifier: MLP, RF, and SVM



Pre-processing Steps

- **Failure Scenario does NOT include failures peculiar to BGP network (injection, hijack, etc…)**
- **Only labeled data (normal/abnormal) are used as the training data**

Problem

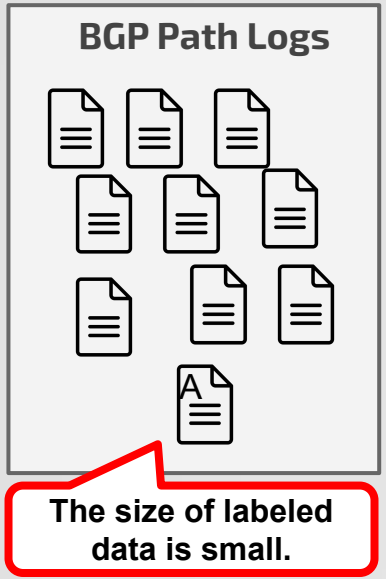
In the case of failure detection in the BGP network,

- **Overfitting to one domain caused by lack of context should occur**
- **Additional dataset is required to apply the model to other networks**

01

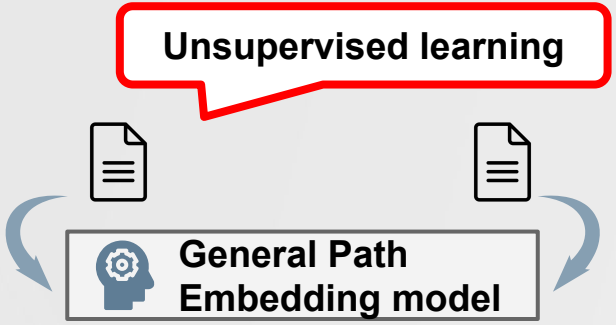
Methodology

Pre-training and fine-tuning approach



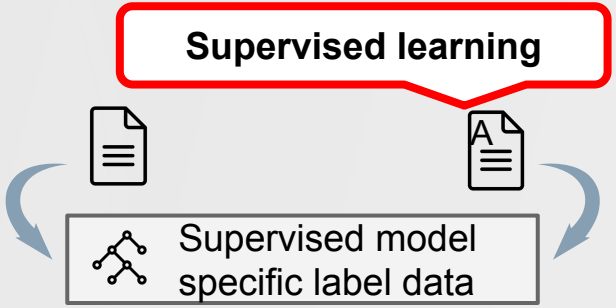
Pre-training phase

We pre-train a general BGP path embedding model to understand BGP context.



Fine-tuning phase

We train a model to predict labels on specific task such as BGP network failure detection.



Advantage

Since the model learning to understand the context does not require specific label data in pre-training, a large amount of BGP path data generated by real network is available.

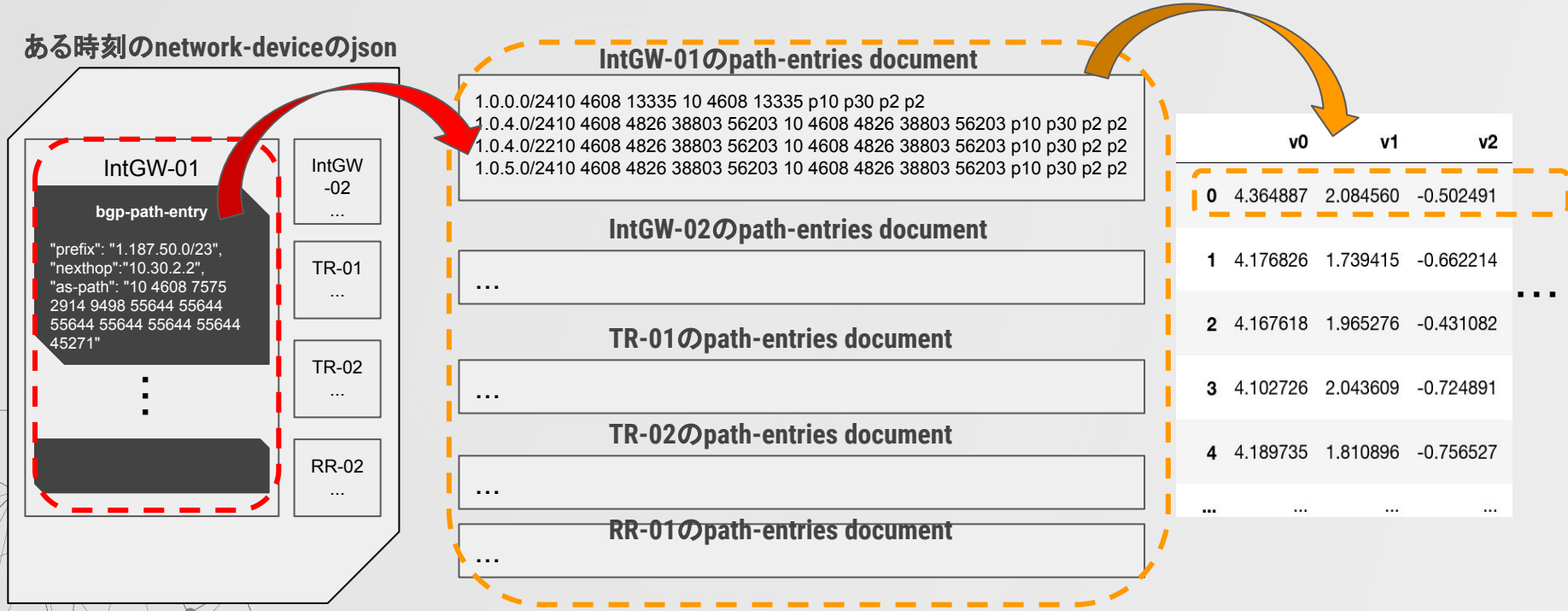
BGP path embedding

Unsupervised learning

BGP path has an ordered structure.

We address the ordered structure as a language model.

We developed a general path model which transforms objects on BGP to vectors.



Dimensionality Reduction

Example Image of Correlation Matrix

https://blog.amedama.jp/entry/2017/04/18/230431

Delete the column with correlation coef. == 1

To cope with the Curse of Dimensionality

Because there are too many columns in the dataframe we need to delete redundant columns.
ex. 238 columns (physical infrastructure)

Method

1. Delete repetitive columns in each row
2. Delete the column with correlation coef. == 1
   - Generated correlation coef. matrix (Left)
   - Pearson product-moment correlation coefficient

$$rho(a,b) = \frac{\sum_{i=1}^{n}(X_{a,i}-\overline{X}_a)(Y_{b,i}-\overline{Y}_b)}{\left\{\sum_{i=1}^{n}(X_{a,i}-\overline{X}_a)^2 \sum_{j=1}^{n}(Y_{b,j}-\overline{Y}_b)^2\right\}^{1/2}},$$

https://jp.mathworks.com/help/stats/corr.html#mw_1b19e0d5-7906-4577-a0a5-b20311da7faf

02

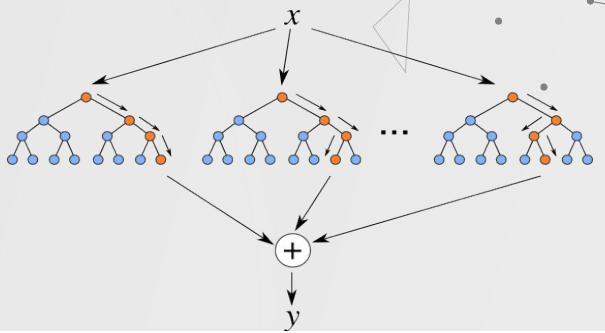
Evaluation

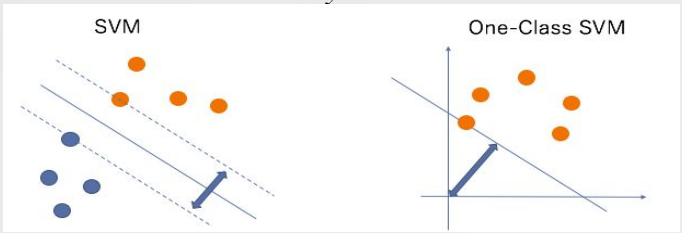
For the Evaluation

Failure Prediction Baseline :

- **Failure detection by tree-based classifiers**
  AdaBoost, Bagging, ExtraTrees, GradientBoosting, Random Forest
  - Regression analysis for the failure indicating column of each failure types
  - Less failure examples problem
    : oversampling by SMOTE
- **One Class SVM** : Unsupervised Learning
  - Learn normal state to detect anomaly status as outlier
  - Useful for unknown datasets
  - Support Vector Machine : Supervised Learning

Example Image of Random Forest
http://kazoo04.hatenablog.com/entry/2013/12/04/175402





Support Vector Machine and One Class SVM
https://www.smartbowwow.com/2018/12/anomaly-detection-using-one-class.html

Evaluation — Tap Loss & Tap Delay

Tap Loss

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	62.90	63.25	**63.27**	63.25	63.25	18.61

Tap Delay

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	53.26	54.83	54.84	**54.86**	54.84	17.38

Evaluation — Node Down & Interface Down

Node Down

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	76.31	71.60	73.62	70.09	73.07	22.93

Interface Down

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	60.92	65.11	65.11	65.12	65.11	10.22

Evaluation — BGP injection & BGP hijack

BGP injection

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	74.34	64.22	61.81	63.63	63.70	1.16

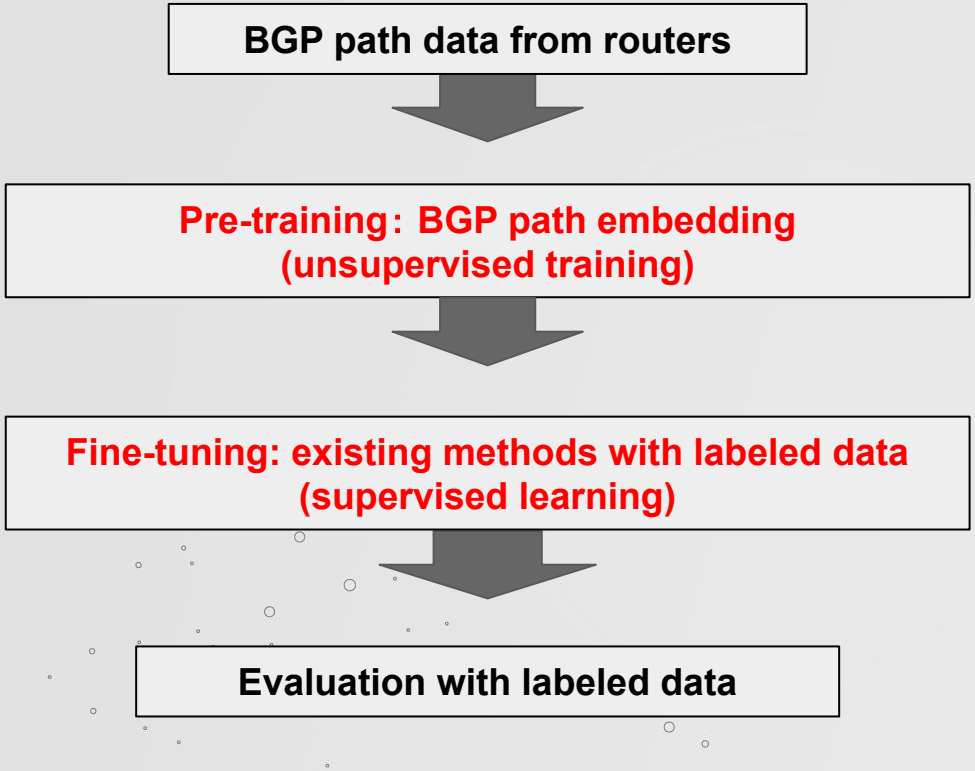
BGP hijack

Method	AdaBoost	Bagging	ExtraTrees	Gradient Boosting	Random Forest	OneClass SVM
f1 score(%)	64.04	54.96	54.56	56.47	56.31	2.07

03

Summary

Summary



Anomaly type	Anomaly name	f1 score
Hardware	Tap Loss	63.27
Hardware	Tap Delay	54.86
Software	Node Down	76.31
Software	Interface	65.11
Software	BGP Injection	74.34
Software	BGP Hijack	64.04

Thanks

- member
  - Ryoma Kondo kondo@mlab.t.u-tokyo.ac.jp
  - Takashi Ubukata t_ubukata@mlab.t.u-tokyo.ac.jp
  - Kentaro Matsuura matsuura@mlab.t.u-tokyo.ac.jp