DATS6301 - Data Mining - Final Project

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Network Intrusion Detection

- Network intrusion: “Any unauthorized activity on a digital network” meant enable malicious activity
- Flow: “Series of communications between two router endpoints bounded by the opening and closing of a session”
- We are looking at the telemetry of flows as they pass from one endpoint to another to try to identify intrusions or attacks on the network

https://www.scnsoft.com/blog/3-levels-corporate-network-security
https://awakesecurity.com/glossary/network-intrusion/
https://www.whatsupgold.com/blog/what-is-network-flow-monitoring

Exploration

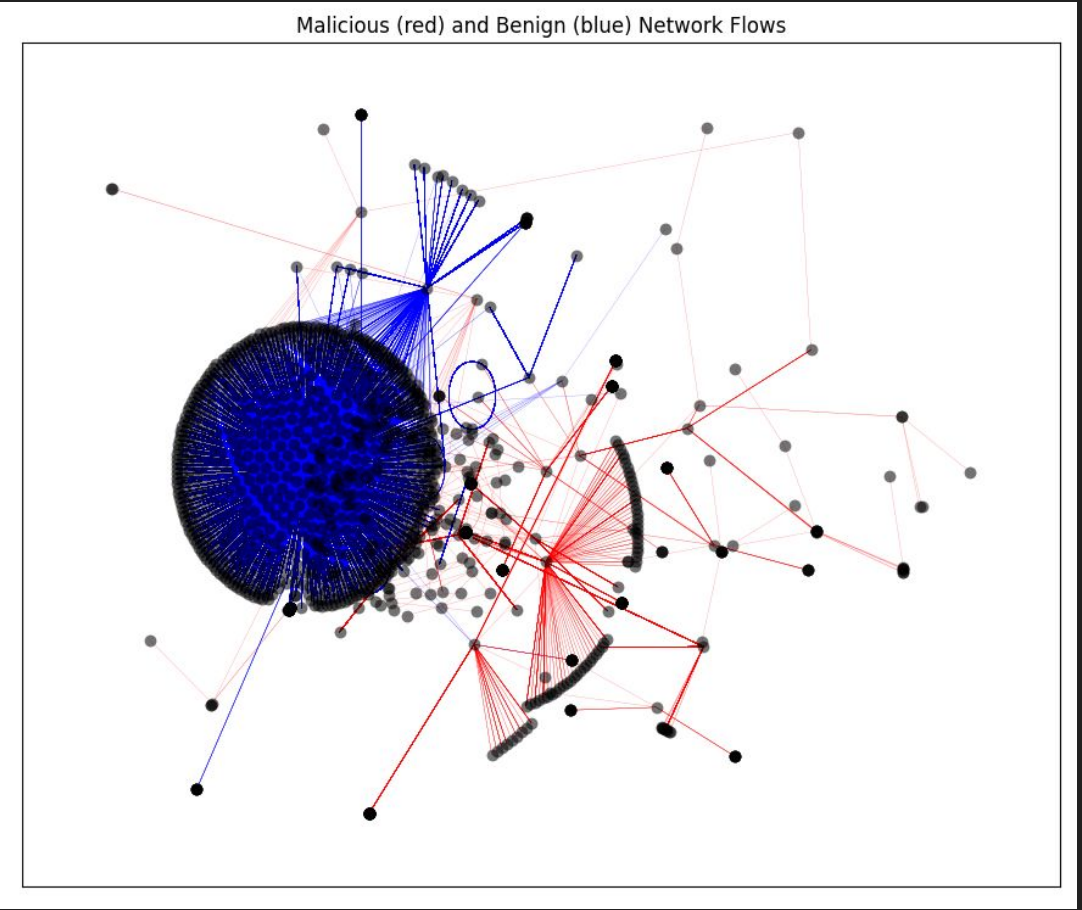
LUFlow Network Intrusion Detection Data Set

- Network flow telemetry measured at Lancaster University
- Spans June 2020 to February 2021
- Sample ~1.5M from 2020 for training and ~300K from 2021 for testing/holdout
- ~31% “malicious” and ~69% “benign” (after dropping “outlier” labels)
- Includes 16 features, such source, destination, protocol, bytes in/out, packets in/out, entropy, time, duration, rate
    - Used 12 features, some engineered, some raw
- No missing values present

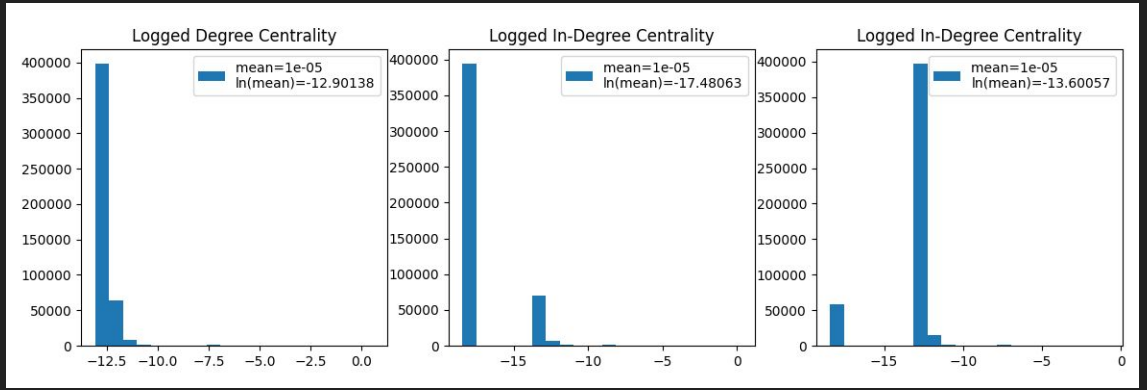
https://www.kaggle.com/datasets/mryanm/luflow-network-intrusion-detection-data-set

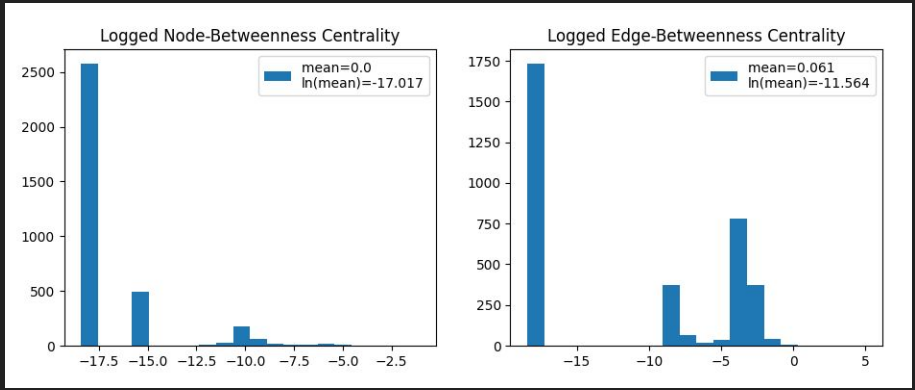
Exploration

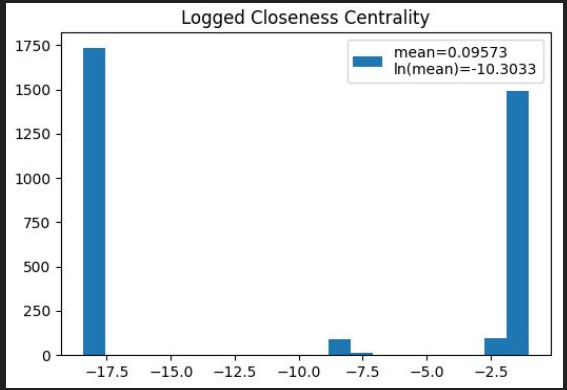
- nodes: 475,033
- edges: 1,441,018
- connections: 479,121
- density: ~6.4E-6
- avg degree centrality: 1E-5
- avg closeness: 0.096
- avg betweenness: 1E-5



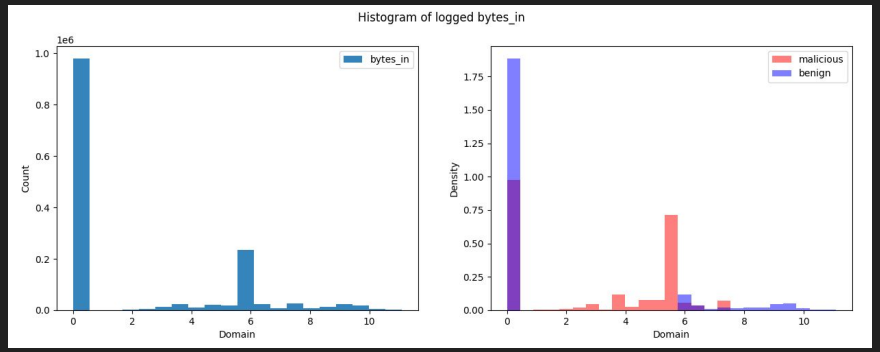
Exploration

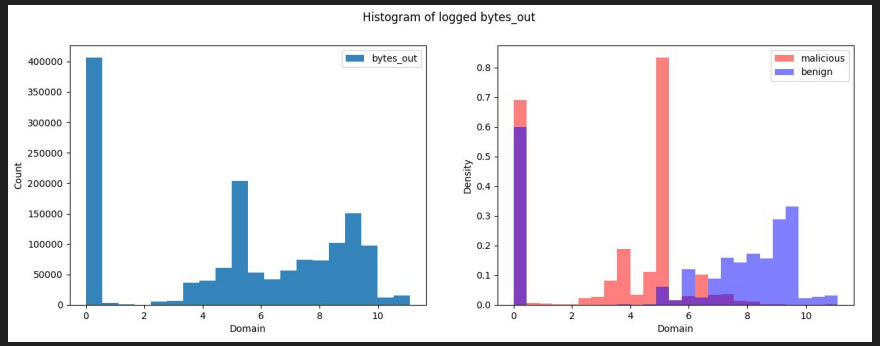


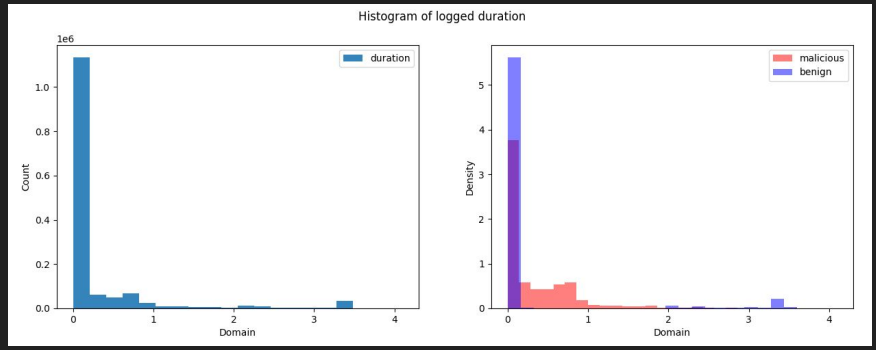


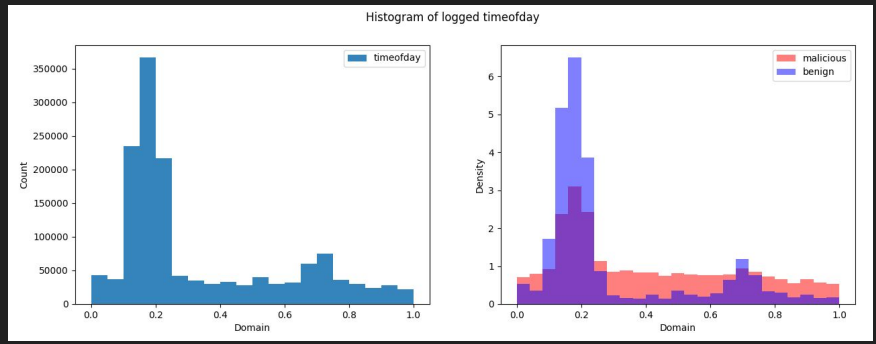


Exploration









Preprocessing steps

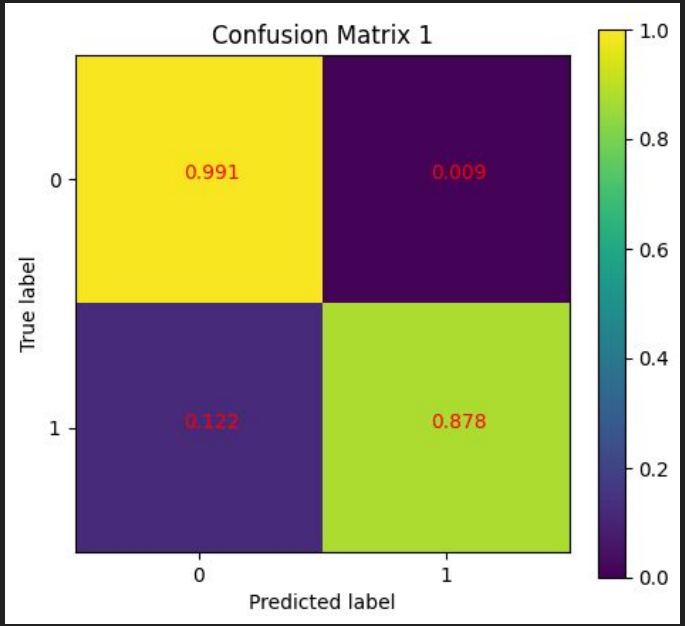
- Create new features from the “start” timestamp to represent “day-of-week” and “time-of-day” of the flow
- Create new “src” and “dst” feature as a concatenation of IP and port
  - Used for building graph, not initial modeling
- One-hot-encode the “protocol” and “day-of-week” categorical features
- Create new “duration” computed from “start” and “end” timestamps
- After some exploration, select subset of original variables for modeling
- Remove observations where label is “outlier”

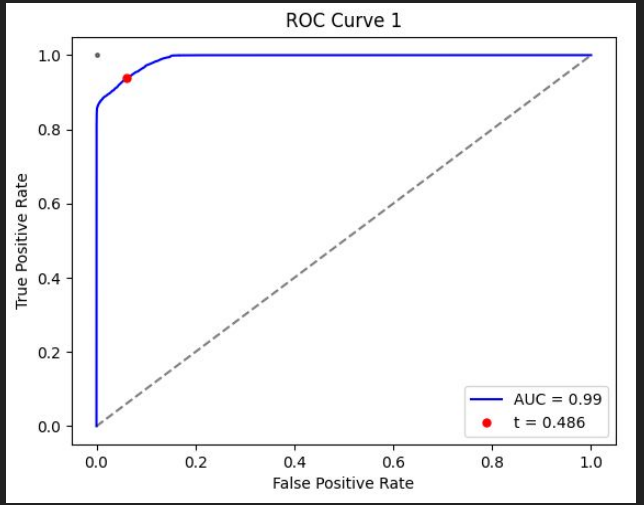
Initial modeling

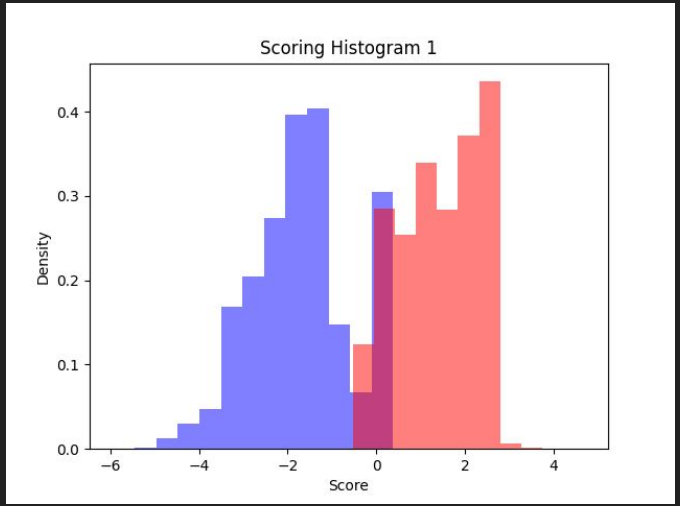
- Three kinds of decision tree ensembles:
  - Random Forest
  - AdaBoost
  - Gradient Boost (with scaling)
- Tune hyper-parameters using grid-search and cross validation, optimizing for ROC-AUC
- Refit model/hyper-parameters with highest score on all the data
- Test on holdout

Modeling

AdaBoost Decision Trees





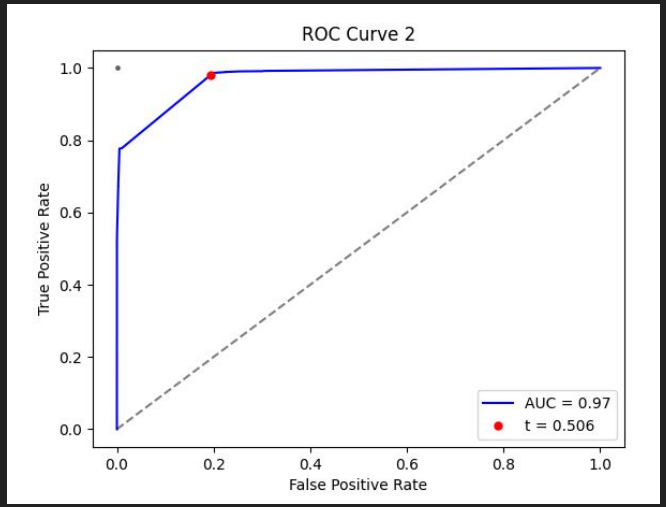


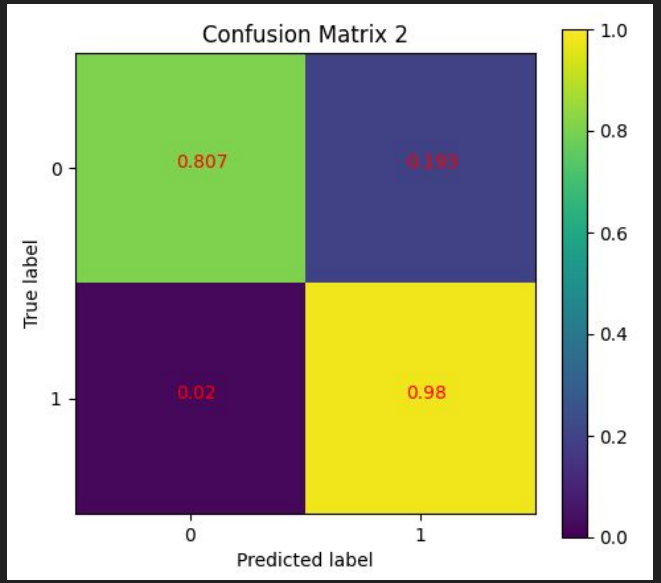
Modeling contd.

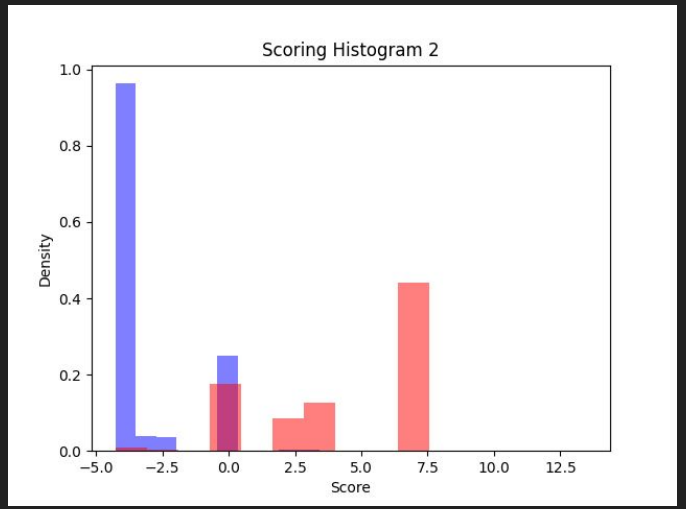
- Why was TNR so much higher than TPR
  - Class imbalance (31% +)?
  - Wrong metric?
- Tune hyper-parameters again using grid-search and cross validation, this time optimizing for recall
- Refit model/hyper-parameters with highest score on all the data
- Test on holdout again

Modeling

AdaBoost Decision Trees
- shallower trees
- balanced instance weights
- lower learning rate







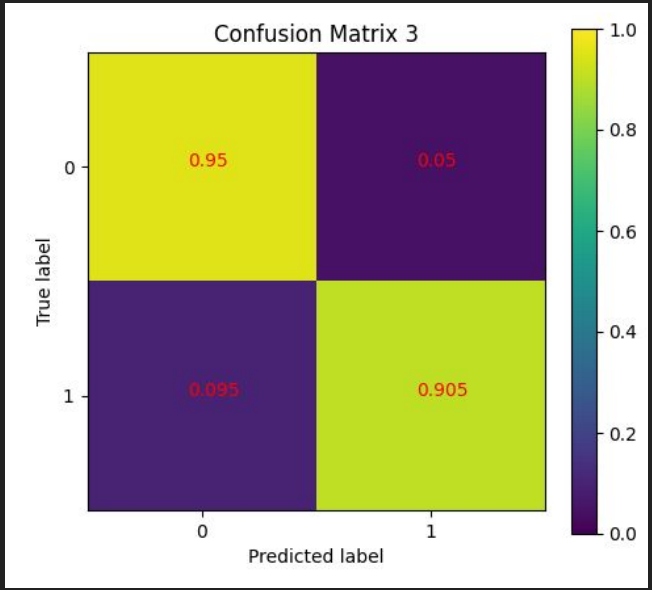
Modeling contd.

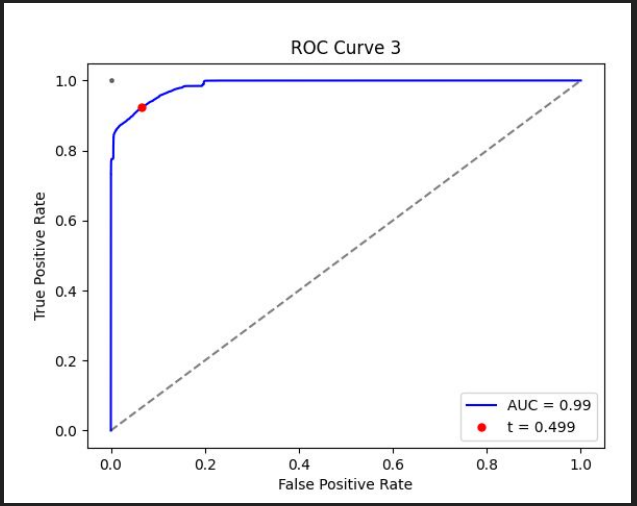
- Why was TPR so much higher than TNR this time
  - Class imbalance over-correction?
- Combining them might even out TPR and TNR
- No training needed, just more evaluation

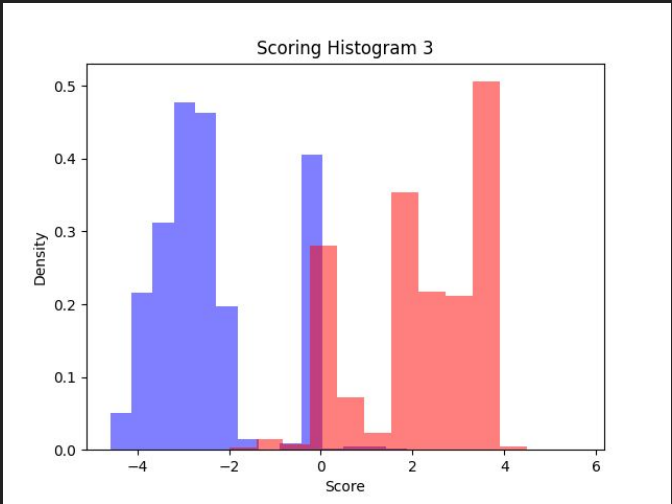
Modeling

Soft Voting Ensemble

- combo of both







Limitations

- Graph structure of data not exploited
- Sample used is only 1% of data available
- Limited domain knowledge

Next Steps

- Node/edge embedding of graph for more model inputs
- Link prediction algorithms
- Graph neural networks
- Scaling