Social Network Analysis with Bot Detection and Adversarial Attacks

This report analyzes how to detect bots in social networks and tests how adversarial attacks can fool these detection systems. I used the Facebook dataset from Stanford SNAP to build a classifier and tested two different types of attacks: Structural Evasion and Graph Poisoning.

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Project Goals

Build a Social Network Graph

From real data.

Create a Bot Detection Model

Using graph features.

Test Adversarial Attacks

How they affect the detection system.

Compare Attack Effectiveness

Which attack works better.

Dataset

- **Source:** Facebook Egonets from Stanford SNAP
- **Description:** Social circles (friends lists) from Facebook users
- **Structure:** Undirected graph representing friendship connections
- **URL:** https://snap.stanford.edu/data/egonets-Facebook.html

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Methodology: Graph Construction and Feature Engineering

The social network was constructed as an undirected graph G = (V, E) where:

- V represents users (nodes)
- E represents friendship connections (edges)

We extracted the following graph-based features for each node:

Structural Features

- **Degree:** Number of direct connections
- **Average Neighbor Degree:** Mean degree of adjacent nodes
- **Clustering Coefficient:** Density of triangles around a node

Centrality Measures

- **Betweenness Centrality:** Frequency of appearing on shortest paths
- **Closeness Centrality:** Average distance to all other nodes
- **Eigenvector Centrality:** Influence based on connections to important nodes
- **PageRank:** Importance score based on network structure

Community Features

- **Community ID:** Membership in detected communities (modularity-based)

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Methodology: Bot Labeling and Baseline Model

How I Labeled Bots

I created labels for bot accounts based on their behavior patterns:

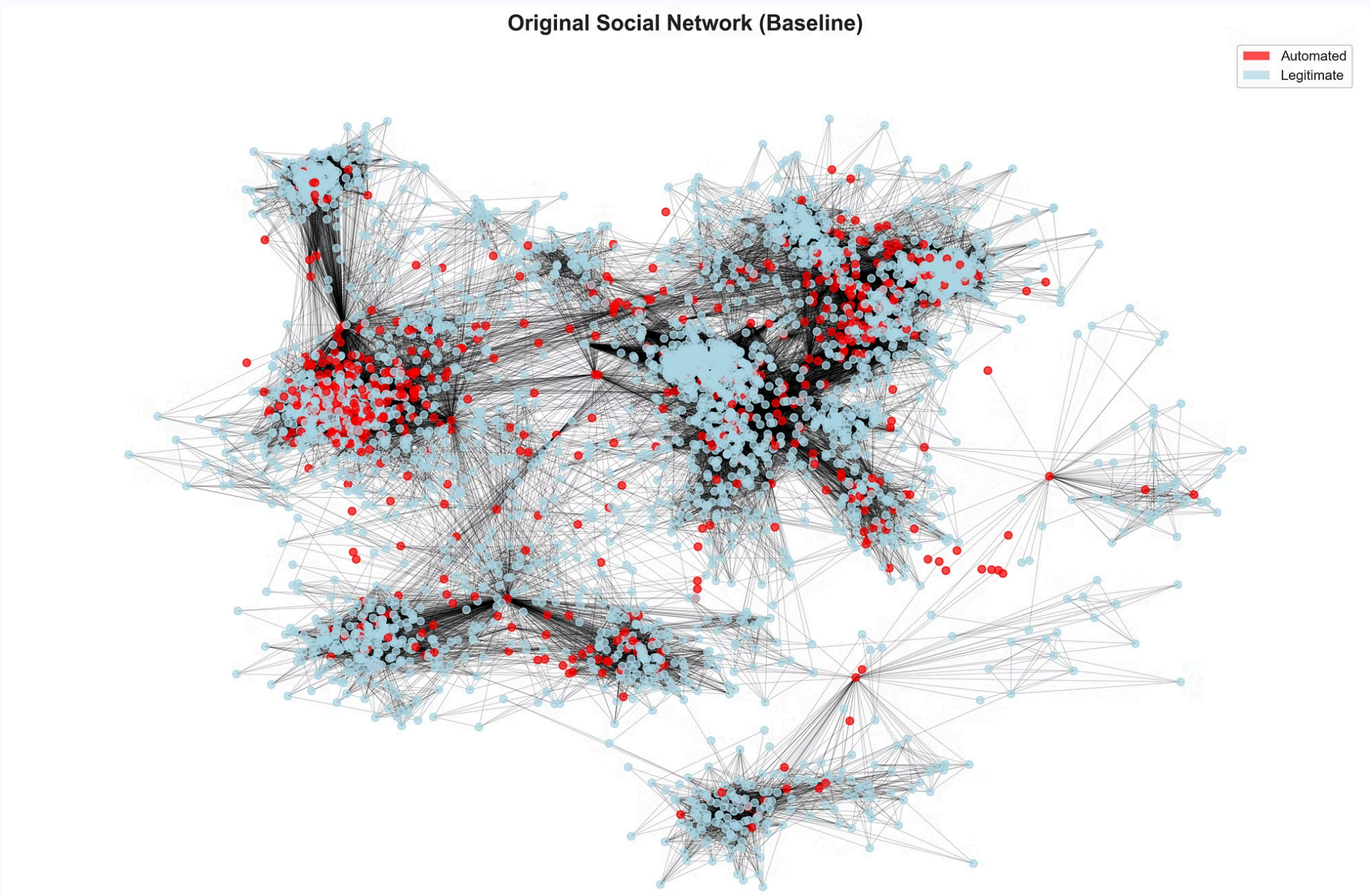
- Low clustering coefficient (not well connected in communities)
- High degree (many connections)
- Low betweenness centrality (not in the middle of the network)

Bot score formula:

```
bot_score = -clustering + 0.5 × (normalized_degree) - 0.3 × betweenness
```

Baseline Model

- **Algorithm:** Random Forest Classifier
- **Parameters:** 100 estimators, max depth 10
- **Features:** All graph metrics except community ID
- **Train/Test Split:** 70/30 with stratification
- **Preprocessing:** Standard scaling



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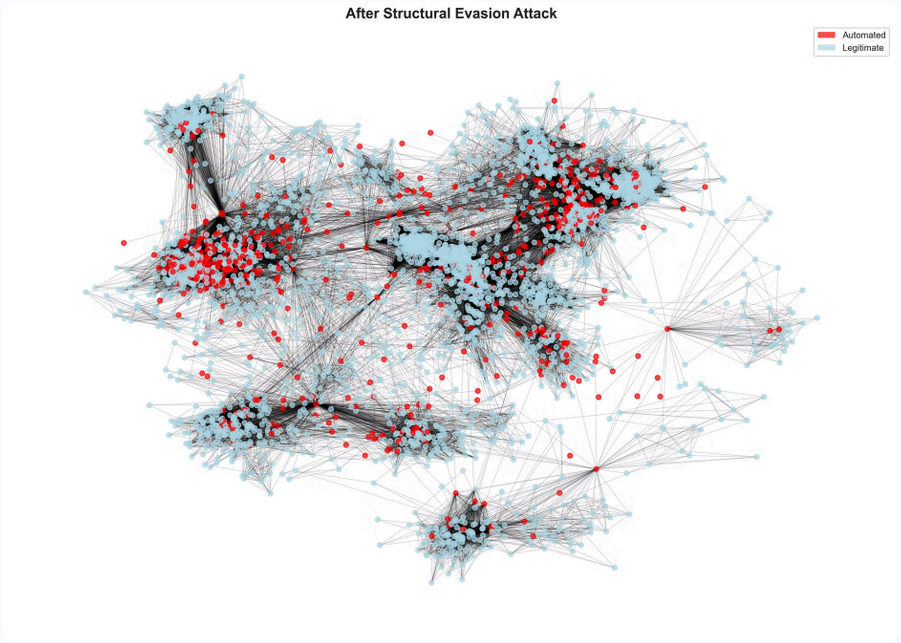
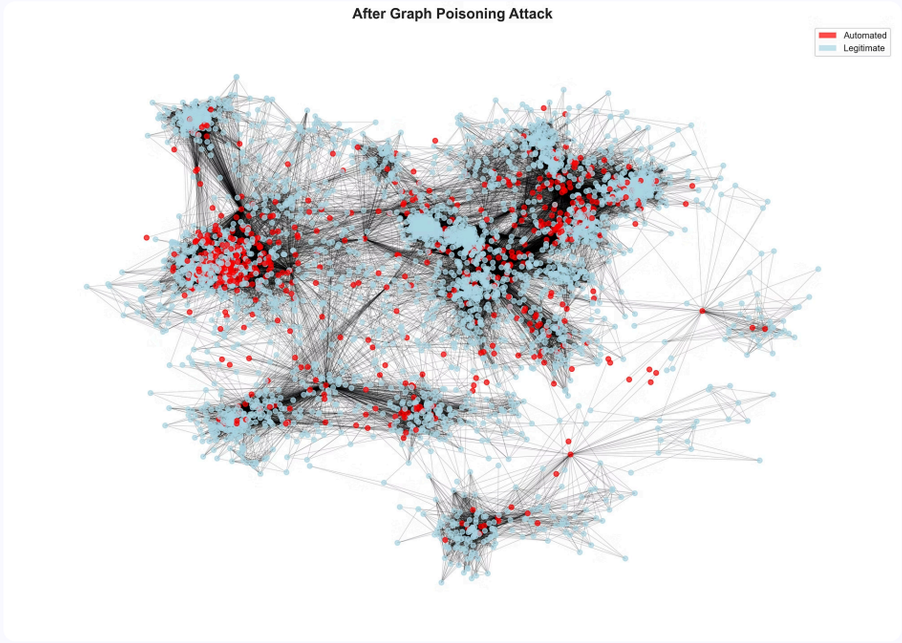
Methodology: Attack Methods



Attack 1: Structural Evasion

This attack changes the graph structure around bot nodes:

1. Add connections to create triangles (increase clustering)
2. Remove some connections to reduce degree
3. Connect to important nodes (look more legitimate)



Attack 2: Graph Poisoning

This attack corrupts the training data:

1. Add fake nodes that look like real users
2. Connect fake nodes to real users
3. Create connections between bots and important users
4. Label fake nodes as legitimate users

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Results: Graph Statistics and Baseline Performance

Graph Statistics

Original Graph:

- Nodes: 4,039
- Edges: 88,234
- Average Degree: 43.69
- Average Clustering Coefficient: 0.606
- Number of Communities: 77

Bot Distribution:

- Total Bots: 605
- Bot Ratio: 15.0%

Baseline Performance

Metric	Legitimate	Automated
Precision	1.00	0.99
Recall	1.00	0.98
F1-Score	1.00	0.99

Overall Accuracy: 99.59%

Feature Importance:

1. Clustering coefficient (local network density)
2. Betweenness centrality (bridging position)
3. PageRank (network influence)
4. Average neighbor degree (connection quality)
5. Eigenvector centrality (connection to important nodes)

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Results: Post-Attack Performance

After Structural Evasion:

Metric	Legitimate	Automated
Precision	1.00	0.97
Recall	1.00	0.99
F1-Score	1.00	0.98

Overall Accuracy: 99.42%

Accuracy Degradation: 0.17%

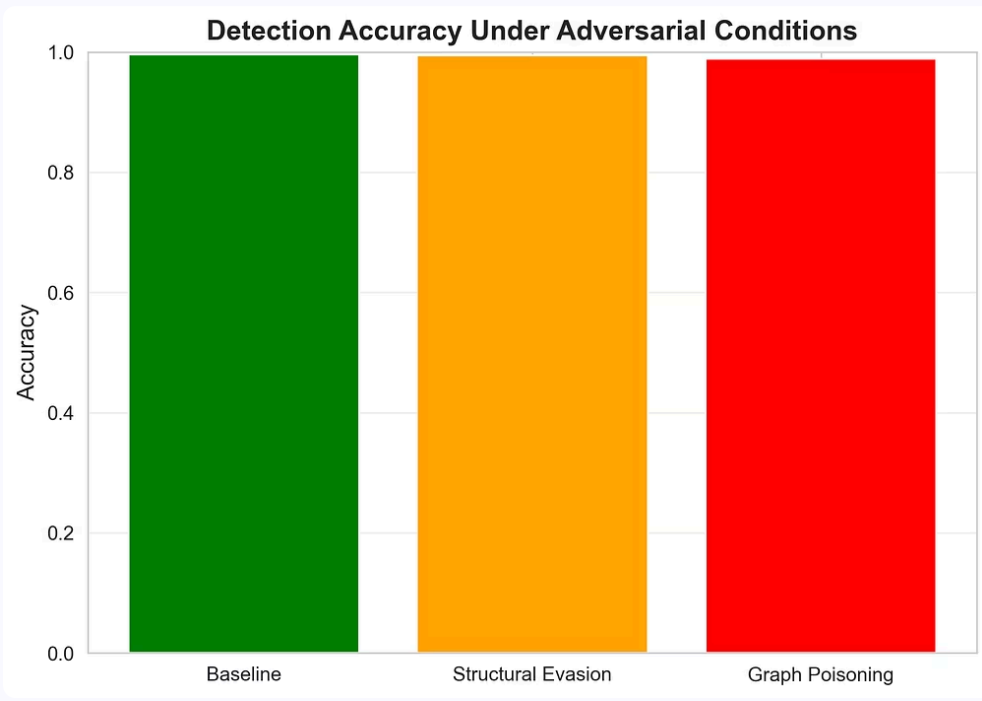
After Graph Poisoning:

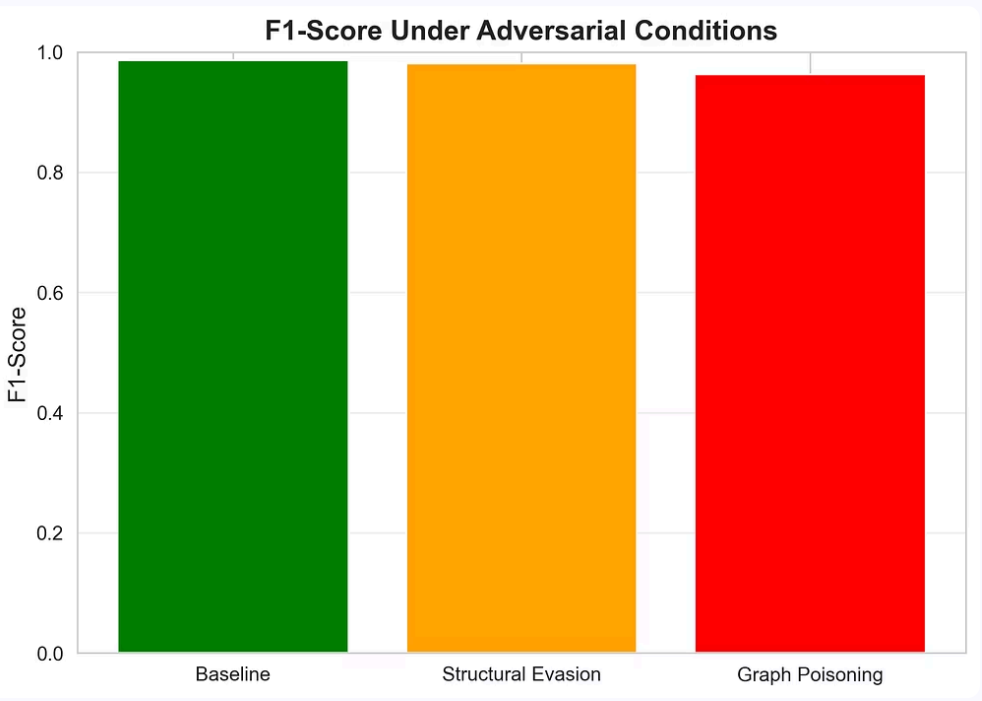
Metric	Legitimate	Automated
Precision	1.00	0.94
Recall	0.99	0.98
F1-Score	0.99	0.96

Overall Accuracy: 98.85%

Accuracy Degradation: 0.74%

Comparative Analysis





Condition	Accuracy	F1-Score	Precision (Bot)	Recall (Bot)
Baseline	99.59%	0.9862	0.99	0.98
Structural Evasion	99.42%	0.9809	0.97	0.99
Graph Poisoning	98.85%	0.9624	0.94	0.98

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Discussion: Impact of Attacks

What I Found - Structural Evasion

- Accuracy dropped by only 0.17%
- Precision for detecting bots dropped from 0.99 to 0.97
- The attack changed 20 bot nodes by increasing their clustering coefficient by 15-25%

What This Means:

- Making bots look more connected to communities helps them hide
- Connecting to important users makes bots seem more legitimate
- The attack worked but only had a small impact overall
- Bots became harder to detect because they looked more like normal users

What I Found - Graph Poisoning

- Accuracy dropped by 0.74%
- Precision for detecting bots dropped from 0.99 to 0.94
- Only 30 changes (15 fake nodes + 15 edges) caused this damage

What This Means:

- Poisoning the training data is more effective than structural evasion
- It was 4.4 times more effective at reducing accuracy
- The fake nodes confused the classifier during training
- This attack affects the model's overall ability to detect bots
- Adding bad data to the training set is a powerful attack

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Discussion: Comparing Attacks and Possible Defenses

Comparing the Two Attacks

Structural Evasion:

Good points:

- Targets specific bots
- Looks like normal network activity
- Doesn't change the overall graph much

Bad points:

- Not very effective (only 0.17% drop)
- Needs to modify many nodes for bigger impact

Graph Poisoning:

Good points:

- More efficient with fewer changes
- Much more effective (4.4x better)
- Affects the whole model

Bad points:

- Might be caught by anomaly detection
- Need to be able to add new nodes
- Fake nodes might be spotted

Possible Defenses

Ways to protect against these attacks:

- Use features that are harder to fake
- Detect unusual changes in the graph structure
- Track user behavior over time
- Use multiple detection methods together
- Clean the data before training

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Conclusion and Future Work

Summary of Results

- The bot detection model achieved 99.59% accuracy
- Structural evasion attack reduced accuracy by 0.17%
- Graph poisoning attack reduced accuracy by 0.74%
- Graph poisoning was much more effective (4.4x better)
- Both attacks made bots harder to detect
- The Facebook network has high clustering (0.606) and 77 communities

What I Learned

- Graph-based classifiers can be fooled by adversarial attacks
- The two attacks exploit different weaknesses
- We need multiple defense strategies to protect against attacks
- Using only graph features isn't enough when attackers are involved

Limitations of This Project

- The bot labels are based on heuristics, not real bot data
- Only used structural features, not content or behavior
- Only tested one type of classifier
- The attacks are simplified versions

Future Work

- Test with real bot datasets
- Try classifiers that are resistant to attacks
- Use Graph Neural Networks
- Combine structural, behavioral, and content features
- Build systems that can adapt to new attacks

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Assignment: Social Network Analysis with Bot Detection

Dataset: Facebook Egonets from Stanford SNAP

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