

Learning with Semantics: Towards a Semantics-Aware Routing Anomaly Detection System

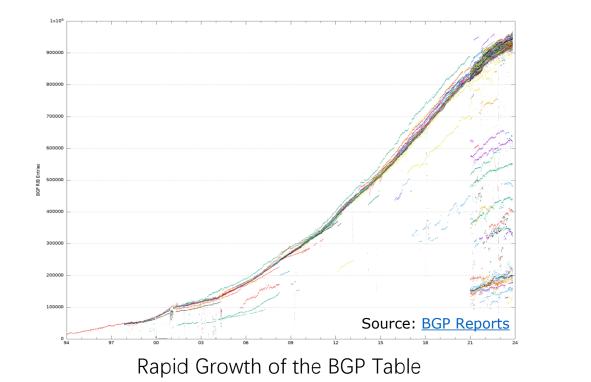
Yihao Chen, Qilei Yin, Qi Li, Zhuotao Liu, Ke Xu,

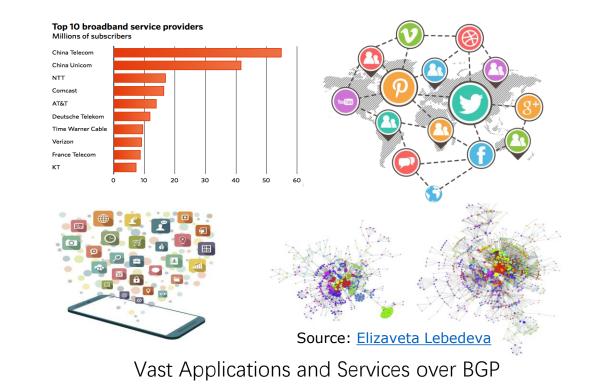
Yi Xu, Mingwei Xu, Ziqian Liu, Jianping Wu



BGP in Today's Internet

- The foundational routing protocol maintaining **global Internet connectivity**.
- Over 960k interdomain routes in operation, supporting more than 75k ASes.





BGP (In)security

- BGP does not guarantee the authenticity and integrity of route announcer
- RPKI and other security extensions, e.g., BGPsec, are **not widely deployed** Anomalies

	Source: The Record							
KLAYswap								
	crypto users lose funds after							
BGP hijac	k							
BGP hijac Hackers have sto								

Loss of Millions in a Single BGP Anomaly



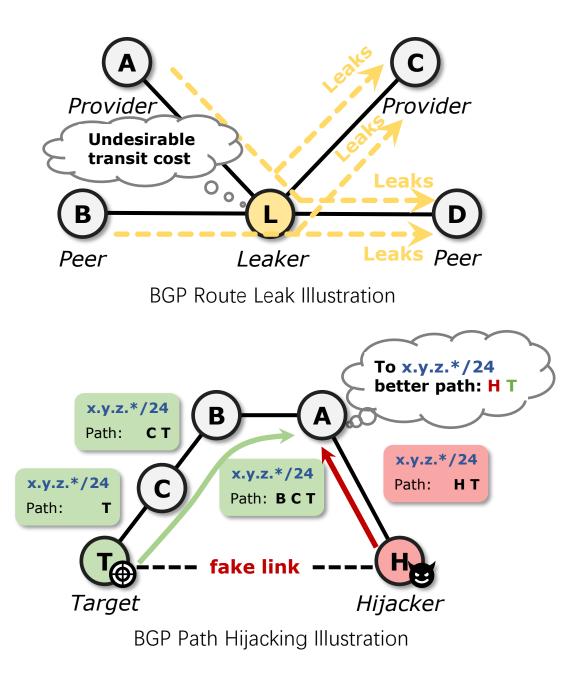
BGP

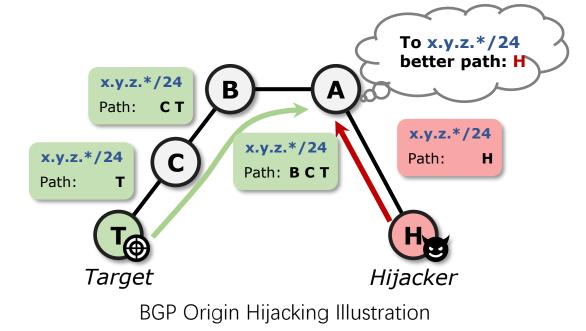
Thousands of BGP Incidents in Q1 2024

BGP routing anomalies are still a major threat to the current Internet!

BGP Routing Anomalies

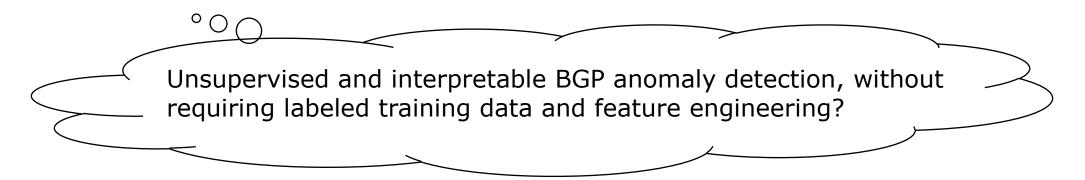
- Typical BGP anomalies
 - BGP hijacking (origin/path)
 - BGP route leak





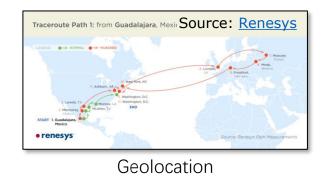
BGP Anomaly Detection

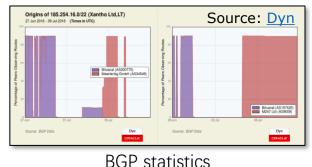
- Traditional methods ARTEMIS [TON'18], HEAP [JSAC'16], Argus [IMC'12], BGPmon [CATCH'09],
 - ➢ Reliance on extensive configuration and/or data probing.
 - ➢ Require significant manual investigation.
 - Limited to specific anomaly types.
- ML-based methods AP2Vec [TNSM'22], Dong et al. [ICNP'21], Hoarau et al. [LCN'21], Testart et al. [IMC'19],
 - Significant training overhead: large-scale **data labeling** and **feature crafting**
 - No BGP semantics embedded -> uninterpretable results



Our Intuition

- Indications of BGP anomalies?
- \Rightarrow Drastic routing path changes.
- Ways to profile the "drasticness"
 - Geolocation? Inaccurate
 - BGP statistics? **VP bias**

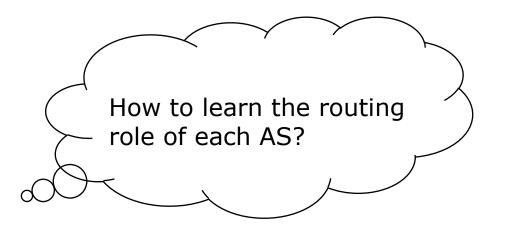




BGP Statistic

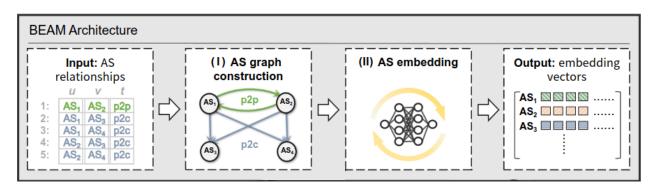
- \Rightarrow A quantifiable representation capable of characterizing an AS's overall routing behaviors.
 - What direct/indirect customers does it serve?
 - What direct/indirect providers does it access?

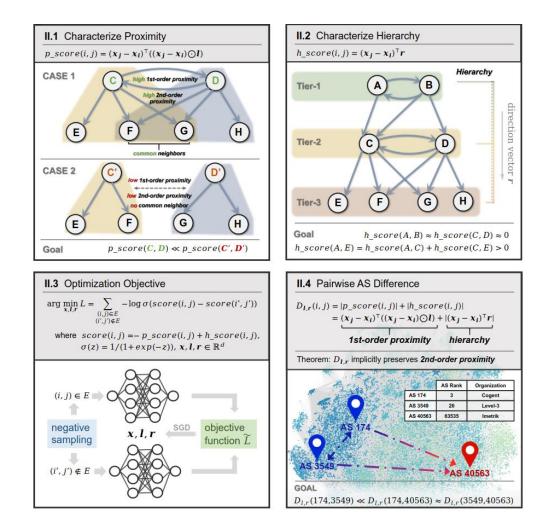
AS Routing Role: An AS's overall routing behaviors, determined by its unique set of routing policies.



Introducing BEAM: An Embedding Model

- BGP sEmAntics-aware network eMbedding
- Routing role: characterize overall relationships
- Two key properties
 - AS Proximity
 - AS Hierarchy
- A dedicated network representation learning model that fully integrates BGP semantics

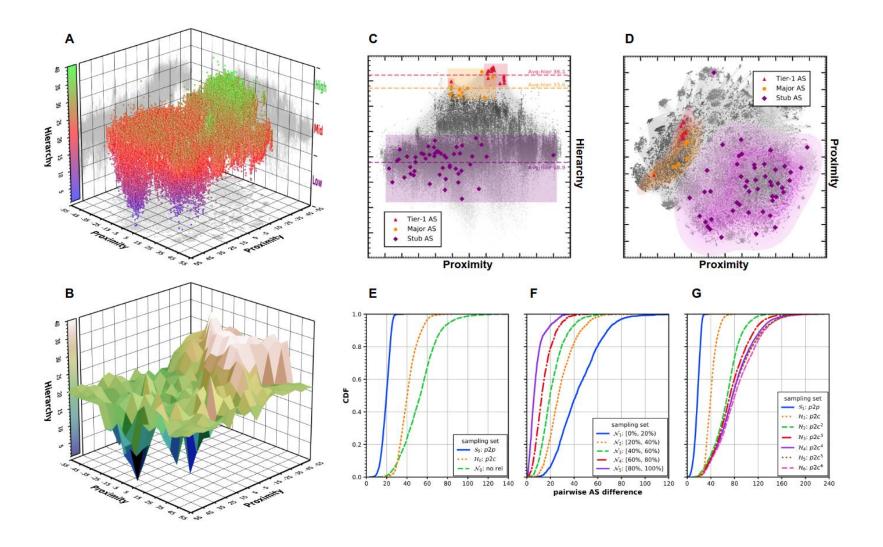




Routing Role Analysis

- 3D Visualization
 - Tier-1
 - Major but not Tier-1
 - Stub
- Pairwise AS Difference
 - 1st-order proximity
 - 2nd-order proximity
 - Hierarchy

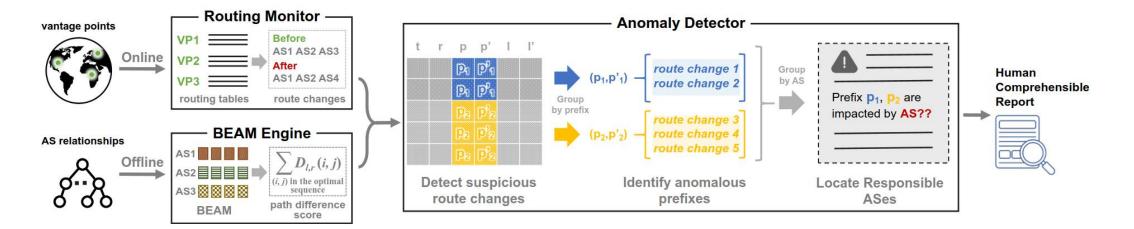
The intrinsic routing characteristics are reserved.



Detection System Based on BEAM

- BEAM engine: offline model training from monthly AS relationships
- Routing monitor: online route monitoring from multiple public vantage points
- Anomaly Detector
 - Detect suspicious route changes with high path difference
 - Identify anomalous prefixes by prefix-indexed grouping
 - Locate responsible ASes by frequent itemset mining





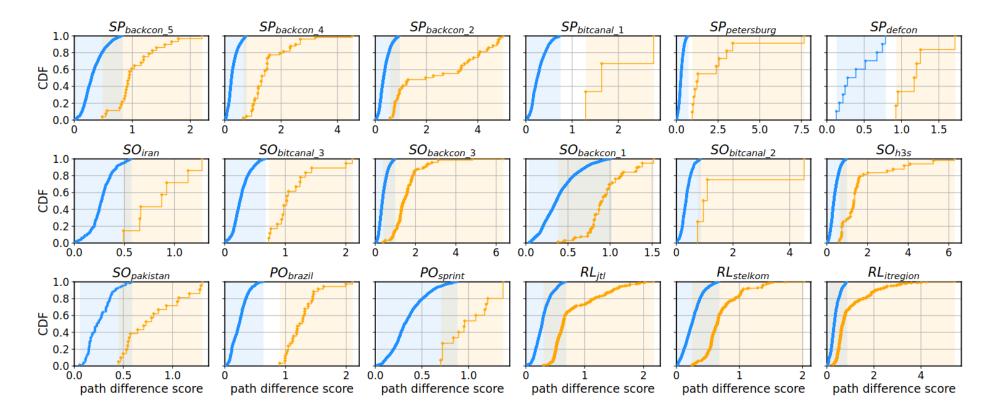
Experiment Setup

- Ground truth: 18 reports on historical incidents spanning from 2008 to 2021
 - 15 BGP hijacking (2 prefix and 13 subprefix hijacking)
 - 3 BGP route leak incidents
 - A total of 11,861,377,951 route announcements
- Baseline
 - 6 variants: Edit Distance, Jaccard Index, Line, Marine, node2vec, SDNE
 - 2 state-of-the-art ML-based system:
 - AV: using word embedding to represent ASN
 - LS: supervised LSTM based detector
- Real-world deployment
 - AS 4134 (rank top-100), China Telecom
 - One-month span of detection since Jan 1 2023



Evaluation: Path Difference Score

• 18 reports on historical routing anomalies spanning from 2008 to 2021



Anomalous route changes show significantly greater path difference.

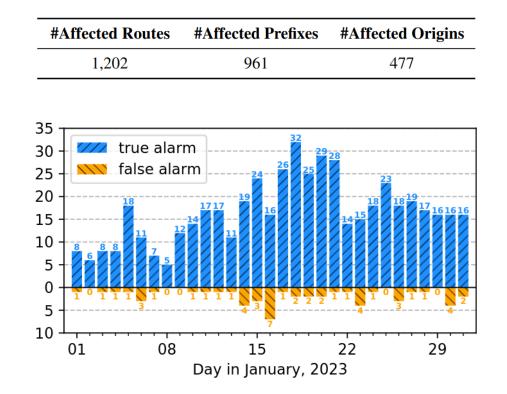
Evaluation: Detection Performance

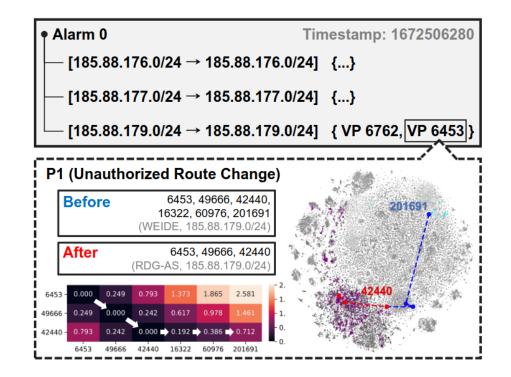
- All 18 anomalies are correctly detected by ours within tens of alarms.
- Ours reports no false alarms for 6 datasets, and only 5 false alarms in the worst case.
- The baselines cannot detect all anomalies and raise more false alarms than ours.
- The baselines require many extra data to train the models.

Dataset	Detected									#Alarms(#FalseAlarms)								
	ED	JI	Li	Ma	NV	SD	LS	AV	Ours	ED	JI	Li	Ma	NV	SD	LS	AV	Ours
SP _{backcon_5}	1	1	✓	✓	✓	×	X	X	✓	18(5)	12(3)	21(4)	15(3)	17(2)	9(1)	62(31)	5(1)	34(2)
SPbackcon_4	1	1	✓	✓	✓	×	1	1	1	14(1)	8(1)	15(2)	13(1)	12(1)	7(1)	42(17)	22(6)	21(0)
SP _{backcon_2}	✓	1	1	✓	1	×	1	X	1	29 (7)	21(7)	24(5)	25(7)	21(4)	8(3)	38(13)	23(18)	37(1)
SP _{bitcanal_1}	X	X	X	✓	1	×	×	X	1	16(0)	16(0)	14(0)	18(0)	17(0)	7(0)	67(36)	30(10)	16(0)
SP _{petersburg}	1	1	✓	✓	1	×	1	1	1	22(3)	14(0)	21(3)	20(1)	16(0)	12(2)	66(28)	37(16)	24(0)
SP _{defcon}	1	1	1	✓	1	×	1		1	7(2)	7(2)	9(3)	9(3)	9(3)	2(2)	28(10)	17(9)	7(1)
<i>SO</i> _{iran}	1	1	✓	✓	1	×	×	×	1	15(1)	8(1)	24(5)	12(2)	16(3)	0(0)	21(11)	19(10)	31(2)
SO _{bitcanal_3}	X	X	X	×	1	×	×	X	1	26(4)	24(3)	29(6)	25(3)	26(5)	7(0)	44(19)	17(8)	40(1)
SO _{backcon_3}	1	1	✓	✓	1	×	×	X	1	32(8)	23(4)	27(6)	34(8)	34(9)	6(1)	49(27)	19(9)	35(5)
SO _{backcon_1}	1	X	1	✓	1	×	×	×	1	19(6)	16(4)	35(14)	18(4)	17(7)	0(0)	63(35)	25(11)	18(3)
SO _{bitcanal_2}	X	1	✓	✓	1	X	X	X	1	16(1)	15(1)	17(2)	15(1)	16(1)	12(2)	39(14)	29(8)	24(0)
SO_{h3s}	1	X	1	✓	✓	×	1	X	1	11(1)	3(0)	15(3)	12(2)	9(0)	5(1)	38(22)	27(8)	14(0)
SO _{pakistan}	1	1	1	✓	1	×	X	×	1	12(4)	8(2)	9(2)	10(4)	8(1)	1(0)	26(14)	2(0)	10(1)
PObrazil	1	1	1	✓	1	×	×	 Image: A start of the start of	1	30(5)	32(4)	30(5)	37(5)	25(3)	11(2)	52(25)	28(11)	51(1)
POsprint	X	X	X	X	X	×	1	X	1	20(0)	18(0)	16(0)	22(2)	19(2)	10(2)	84(24)	33(8)	29(0)
RL _{jtl}	X	X	X	X	X	×	1	X	1	17(1)	16(1)	21(2)	16(2)	17(1)	6(3)	60(40)	21(11)	46(5)
RL stelkom	X	✓	X	×	X	×	✓	X	1	25(4)	21(2)	34(6)	26(3)	23(3)	4(0)	284(225)	17(8)	43(3)
RL _{itregion}	X	X	X	×	X	×	1	X	1	25(0)	21(1)	23(0)	20(0)	21(3)	6(2)	74(44)	23(9)	44(4)
Overall	11/18	11/18	12/18	13/18	14/18	0/18	9/18	4/18	18/18	354(53)	283(36)	384(68)	347(51)	323(48)	113(22)	1137(635)	394(161)	524(29)

Real-World Deployment

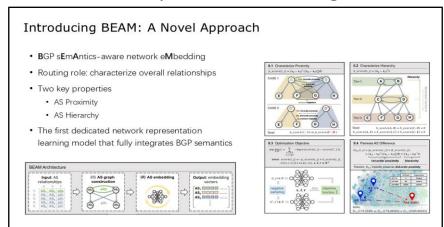
- Deployed in AS 4134 of China Telecom, detecting from January 1 to February 1 2023
- 152,493,303 live route announcements, 5,106,442 route changes, and 548 raised alarms.
- On average, 17.68 alarms per day, including **1.65 false alarms**.



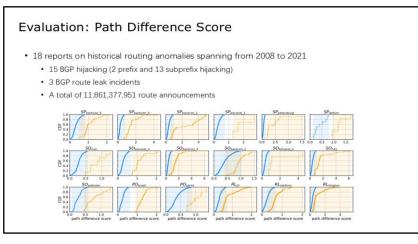


Summary

Intuition: represent AS routing roles



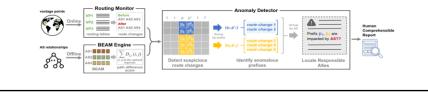
Evaluation: over 11 billion announcements



Workflow: learning, detection, interpretation

Anomaly Detection System

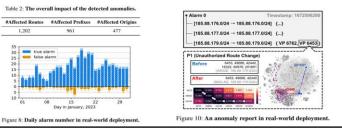
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Deployment: large ISP real-world deployment

Real-World Deployment

- Deployed in a large ISP (top 100), detecting from January 1 to February 1 2023
- In total, the system processes 152,493,303 live route announcements, detects 5,106,442 route changes and raises 548 alarms.
- On average, 17.68 alarms per day, including 1.65 false alarms.





Thank you!

Key Takeaways

- AS routing roles capture overall routing behaviors of ASes.
- Routing anomaly detection can be achieved by detecting routing role churns.
- Our system can detect previous confirmed anomalies with minor false alarms.
- Routing-role change analysis enables visually interpretable anomaly alarms.

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Code: <u>https://github.com/yhchen-tsinghua/routing-anomaly-detection</u>

