Constructing Flow Graphs from Procedural Cybersecurity Texts

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COR : Yamakata et al., 2020
MAM : Qian et al., 2020

Motivation

- **Challenges** of procedural texts written in free natural language form
  - Hard to follow,
  - Difficult to visualize interactions between sentences
  - Difficult to extract inferences
  - Hard to track states of an object or a sub-task

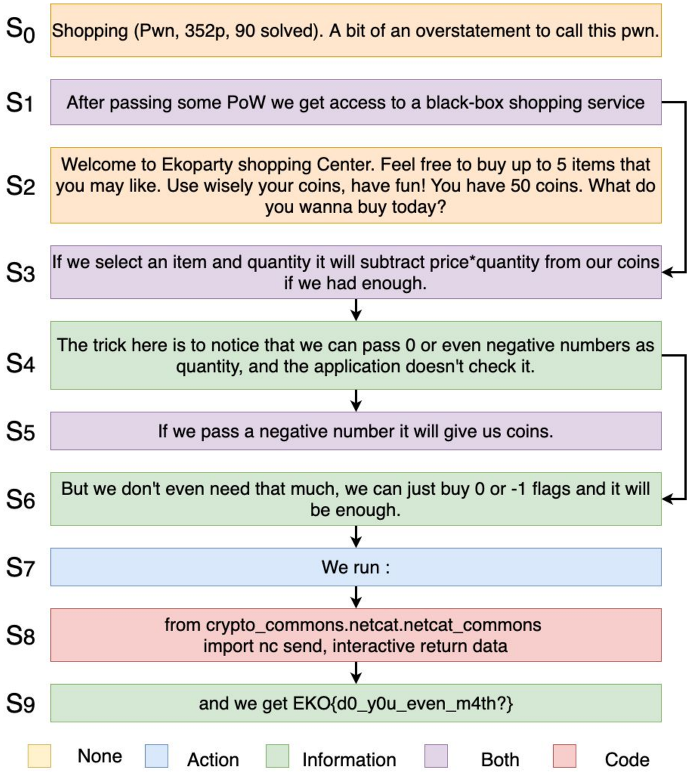
- **Goal** : Provide flow-structures to free form natural language texts
  - ***Cybersecurity(CTFW)***, Cooking instruction(COR), maintenance manual domains(MAM)

- **Flow-Structure** of the Procedural Text:
  - Sentence level dependencies leading to a goal (action traces, effects of an action, information leading to the action, and instruction order)

Flow-Structure Example

- **CTFW (3154) (New dataset)**
  - Cybersecurity write-ups from Catch The Flag (CTF) competitions
  - Participants find and exploit vulnerabilities in a given set of software services
  - They publish the details of how they exploited the services

- S_1, S_3, S_4 : Author's observation about nature of service
- S_5, S_6 : possible courses of action
- S_6, S_7, S_8 : chosen path to exploit the vulnerability
- S_0, S_2 : Irrelevant information



CTFW Dataset

- **How structure helps in cybersecurity ?**
    - Automated Vulnerability Discovery and mitigation
    - Automated Exploit generation,
    - Security education in general

- **Annotations:**
    - Sentence Type : Action (A), Information (I), Both (A/I), Code (C), None.
    - Flow-Structure : Connection between a pair of sentences based on the interaction between them

Flow-Structure Generation Approach

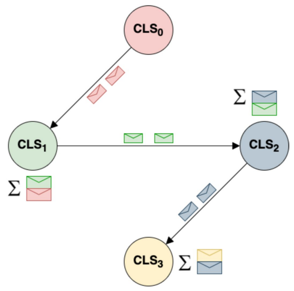
- **Segment Document to Sentences**
  - Rule-based segmentation into sentences
  - Relevant sentence identification
  - $D_i = \{S_0, S_1, S_2 ... S_{n-1}\}$

- **Graphical Representation of Document**
  - Each relevant sentence as a graph node
  - Sentence Windowing (W_N) where N = {3, 4, 5, all}
  - Graph Connections are directed edges from S_i to S_j where $i < j$.
  - In each window,
    - *Linear* : S_i to S_{i+1}
    - *Semi-Complete* : S_i to $\{S_{i+1}, \ldots S_{i+N}\}$

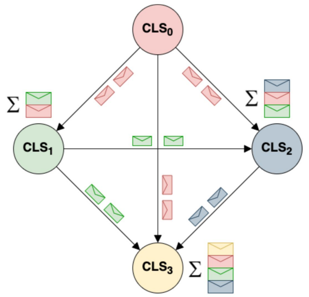
Approach (Contd.)

- **Node Feature learning**
  - Initial Node features from BERT/ RoBERTa
  - $h_{S_i} = \text{BERT}([\text{CLS}]s_0 s_1 \ldots s_{n-1}[\text{SEP}])$

- **Neighbor-aware node feature learning**
  - GCN and GAT learns richer node representations through message passing
  - Linear connections learn from its predecessors
  - Semi-Complete connections learn based on all the previous nodes in a Window



Linear



Semi-Complete

Experiments - Sentence Classification Baseline

Model	Val	Test
BERT-Base	78.48±0.25	77.42±0.10
BERT-Large	78.19±0.48	77.13±0.20
RoBERTa-Base	78.85±0.25	77.37±0.11
RoBERTa-Large	79.02±0.16	**77.66±0.12**

- Preprocessing and segmentation into sentences
- We modeled this as a text classification task with five classes :
  - Action (A), Information (I), Both (A/I), Code (C), None.
- We consider any sentence with Action or Information or Both as relevant and rest as irrelevant

Experiments - Flow Structure Prediction

	Models	CTFW		COR		MAM	
		PRAUC	F1	PRAUC	F1	PRAUC	F1
Baselines	Random	-	50.49	-	42.78	-	47.82
	Weighted Random	-	37.81	-	39.13	-	44.10
	BERT-NS	0.5751	26.12	0.5638	43.14	0.5873	29.73
	RoBERTa-NS	0.5968	32.44	0.5244	42.99	0.6236	39.65
Ours	BERT-GCN	0.7075	69.26	**0.6312**	58.13	**0.6888**	63.75
	RoBERTa-GCN	**0.7221**	69.04	0.6233	61.44	0.6802	65.73
	BERT-GAT	0.5585	61.93	0.4553	41.93	0.4568	62.18
	RoBERTa-GAT	0.5692	64.51	0.4358	24.74	0.4585	59.55

- PRAUC scores for both LM-GCN versions are better than baseline next sentence prediction task (LM-NS)
- LM-GAT underperforms

Effect of Graph Connection Type

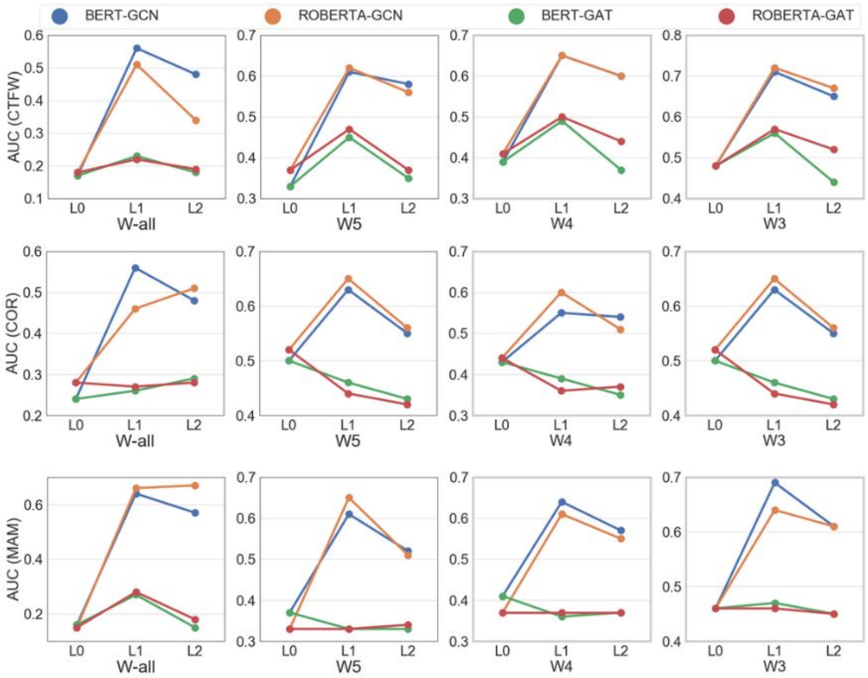
	W_3	W_4	W_5	W_{all}
CTFW-SC	0.6630	0.5985	0.5733	**0.5590**
CTFW-L	**0.7221**	**0.6520**	**0.6150**	0.3962
CTFW-EP	0.3700	0.2900	0.2400	0.0700
COR-SC	0.5639	0.5129	0.4731	**0.5580**
COR-L	**0.6456**	**0.6012**	**0.5274**	0.4034
COR-EP	0.3700	0.3100	0.2600	0.1700
MAM-SC	0.6528	0.6219	0.6091	**0.6718**
MAM-L	**0.6888**	**0.6362**	**0.6137**	0.4161
MAM-EP	0.4500	0.3700	0.3200	0.1500

- For each Window, best model performs better than the baseline PRAUC scores (EP)
- Linear connections works better with smaller windows
- Semi-complete connections works better for W_{all}

Effect of Graph Layers

- Single GNN layer have better performance

- Increasing graph layers reduces the performance across all 3 datasets



Conclusion

- Introduced a new procedural sentence flow extraction task from natural language texts
- We create a sufficiently large procedural text dataset in the cybersecurity domain (CTFW) and construct structures from the natural form
- We empirically show that this task can be generalized across multiple domains with different natures and styles of texts

Thank You !!!

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Paper : https://arxiv.org/abs/2105.14357

Code : https://github.com/kuntalkumarpal/FlowGraph

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