DitDetector: Bimodal Learning based on Deceptive Image and Text for Macro Malware Detection

Jia YAN, Ming WAN, Xiangkun JIA, Lingyun YING*, Purui SU* and Zhanyi WANG

TCA/SKLCS, Institute of Software, Chinese Academy of Sciences

School of Cyber Security, University of Chinese Academy of Sciences

School of Computer Science and Technology, University of Chinese Academy of Sciences

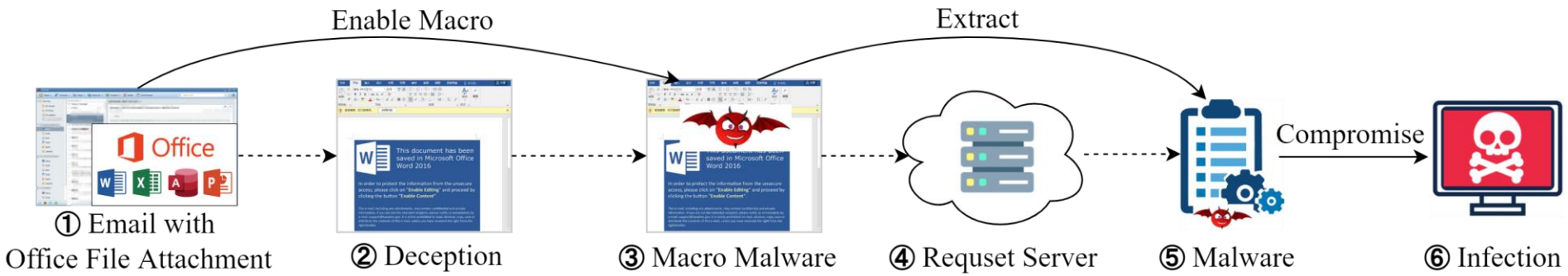
QI-ANXIN Technology Group Inc.

Macro Malware

- Macro
  - Embedded in Microsoft Office Suite
  - Functionality, automate repetitive tasks

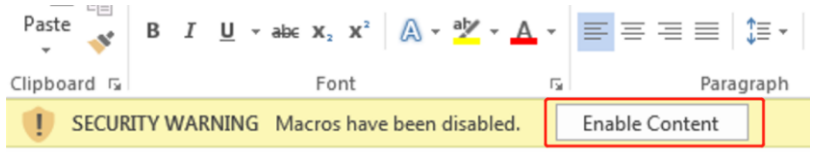
```
(General)
Sub proFirst()
        Range("A1").Value = 34
        Range("A2").Value = 66
        Range("A3").Formula = "=A1+A2"
        Range("A1").Select
End Sub
```

- Malware
  - Easily write and obfuse
  - Download attack payload or run itself



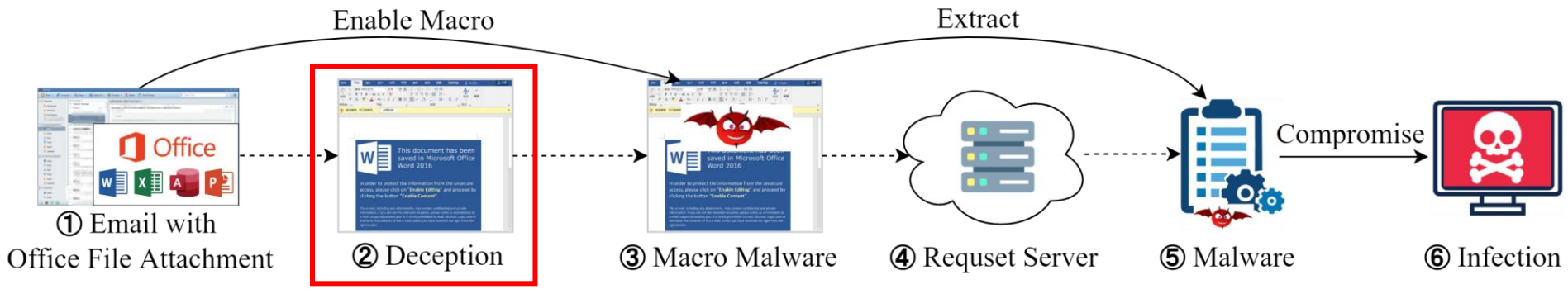
Macro Malware

- Defense
  - Default disable-disable strategy



- Deceptive Information

- Detection
  - Spam filtering
  - Document analysis
  - Traffic analysis
  - Runtime detection



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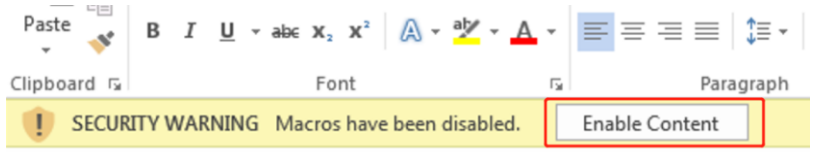

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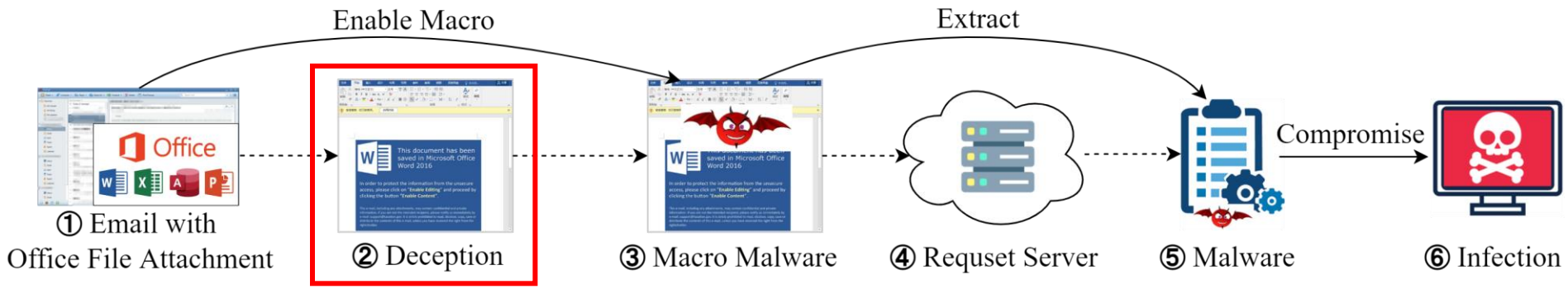

Macro Malware

- Document analysis
  - Signature
    - Specific strings
  - File metadata
    - Structural feature extraction
  - Macro code
    - Plain text
    - Machine Learning Algorithm
  - Deceptive information
    - Keyword hits
    - Visual element matching

- Challenges
  - Variants evasion
  - Different types of file formats
    - Compound File Binary (CFB)
    - Office Open XML (OOXML)
  - Multiple types of macros
    - VBA macro
    - Excel 4.0 macro
  - Advance malware
    - Remote template injection

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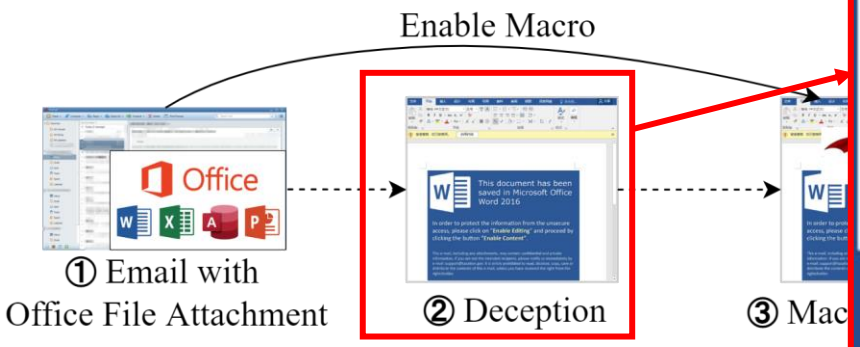
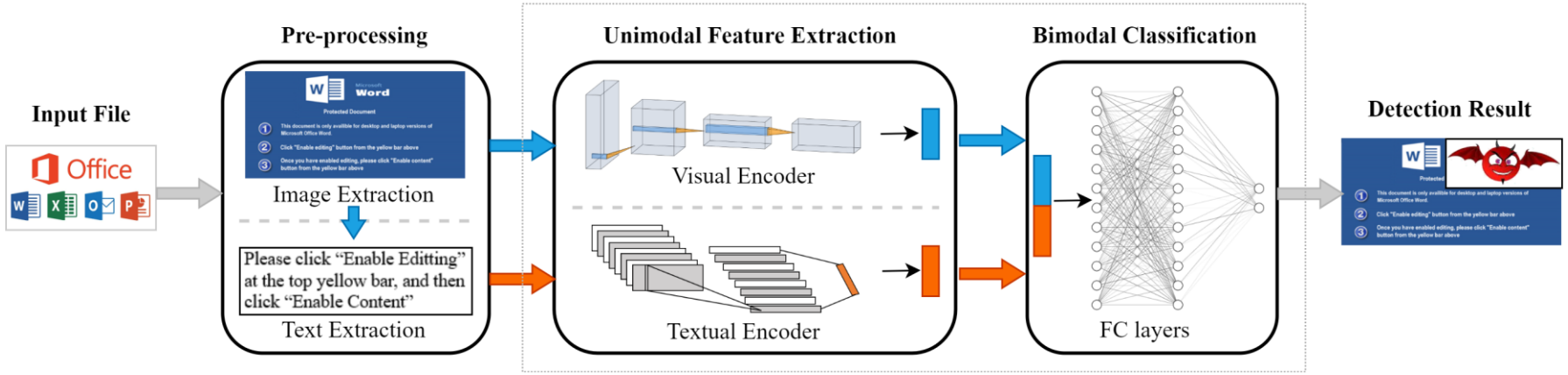


DitDetector

A bimodal learning-based detector, to detect deceptive information

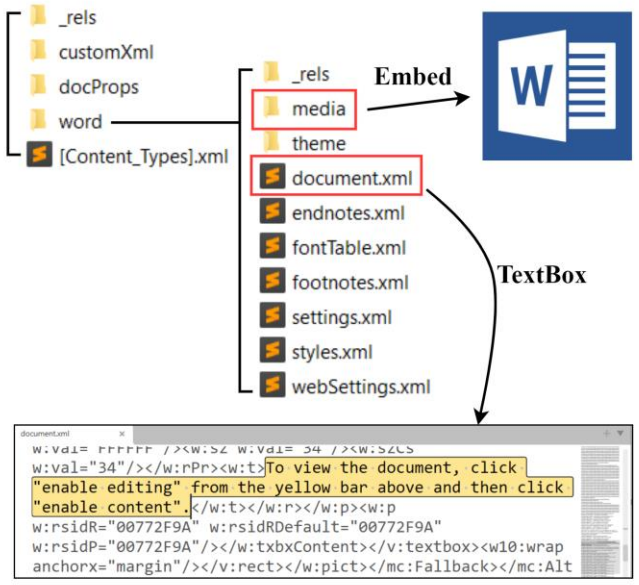
- End to end
- Complementarity
  - Image
  - Text

- Pre-processing
- Unimodal Feature Extraction
  - Visual Encoder
  - Textual Encoder
- Bimodal Classification



Pre-Processing

- Decompress document
  - Multiple independent individuals
  - File formats limitation
    - OOXML ✓
    - CFB ×



- Preview image extraction
  - Oracle open-source tool
  - Get the layout and complete information

Pre-Processing

- Text Extraction
  - Challenge
    - File fromat limitation
    - Text embeds in image
  - Solution
    - Optimical Character Recognition
    - e.g., Tesseract

Detection

- Visual encoder
  - MobileNetV3-Small[1]

Input	Operator	exp size	#out	SE	NL	s
224*224*3	conv2d, 3*3	-	16	-	HS	2
112*112*16	bneck, 3*3	16	16		RE	2
56*56*12	bneck, 3*3	72	24	-	RE	2
28*28*24	bneck, 3*3	88	24	-	RE	1
28*28*24	bneck, 5*5	96	40		HS	2
14*14*40	bneck, 5*5	240	40		HS	1
14*14*40	bneck, 5*5	240	40		HS	1
14*14*40	bneck, 5*5	120	48		HS	1
14*14*48	bneck, 5*5	144	48		HS	1
14*14*48	bneck, 5*5	288	96		HS	2
7*7*96	bneck, 5*5	576	96		HS	1
7*7*96	bneck, 5*5	576	96		HS	1
7*7*96	conv2d, 1*1	-	576		HS	1
7*7*576	pool, 7*7	-	-	-	-	1
1*1*576	conv2d 1*1, NBN	-	1280	-	HS	1
1*1*1280	conv2d 1*1, NBN	-	k	-	-	1

- Text encoder
  - TextCNN[2]

$$z'_{ks} = \text{Conv1D}(x_t, ks), \quad ks = 3, 4, 5$$

$$z_{ks} = \text{MaxPooling}(z'_{ks}), \quad ks = 3, 4, 5$$

$$z_t = z_3 \oplus z_4 \oplus z_5$$

- Bimodal Classification
  - Joint representation
    - Visual representation
    - Textual representation
  - 2 fully connetecd layers

[1] Howard, Andrew, et al. "Searching for mobilenetv3." *Proceedings of the IEEE/CVF international conference on computer vision*. 2019.

[2] Zhang, Ye, and Byron Wallace. "A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification." arXiv (2015).

Evaluation

- Setup
  - Three dataset
    - MalDoc[3]
    - XL4 Macro
    - RTInjection

MalDoc	Malicious	Benign	Total
Original	15105	2735	17840
Reduced	13260	2709	15969

Dataset	Malicious	Type	Collection time
XL4 Macro	1504	Excel 4.0 macro	20220101-20220430
RTInjection	510	CVE-2017-0199	20220101-20220430

- Experiments
  - Ablation Study
    - Textual detection
    - Visual detection
    - Bimodal detection - DitDetector
  - Compare with methods
    - 4 state-of-the-art(SOTA) ML models
      - RFC, MLP, SVC and XGBoost
    - 5 AntiVirus engines
      - Kaspersky, Symantec, Microsoft, McAfee and Sophos

[3] Vasilios Koutsokostas, et al. Malicious MS Office documents dataset. https://doi.org/10.5281/zenodo.4559436

Evaluation on MalDoc

- DitDetector outperforms better on ablation study

Model	Precision	Recall	Accuracy	F1-score
TextCNN	0.9791	0.9782	0.9782	0.9785
MobileNetV3	0.9473	0.9434	0.9434	0.9402
DitDetector	**0.9935**	**0.9935**	**0.9935**	**0.9934**

- DitDetector does not lose the performance

Model	Precision	Recall	Accuracy	F1-score
MLP	0.9906	0.9904	0.9904	0.9905
RFC	0.9910	0.9909	0.9909	0.9910
SVC	0.9896	0.9895	0.9895	0.9895
XGBoost	0.9805	0.9798	0.9798	0.9800
DitDetector	**0.9935**	**0.9935**	**0.9935**	**0.9934**

(a) Visual information

(b) Textual information

Estonian deceptive information

Evaluation on Real-world Dataset

- DitDetector outperforms robust

Dataset	MLP	RFC	SVC	XGBoost	*DitDetector*
MalDoc	0.9905	0.9910	0.9895	0.9800	**0.9934**
XL4 Macro	0.2358	0.6927	0.9405	0.9537	**0.9993**
RTInjection*	–	–	–	–	**0.9990**

- DitDetector performs better than AV engines

Dataset	Kaspersky	Symantec	Microsoft	McAfee	Sophos	*DitDetector*
Maldoc	0.9684	0.8988	0.9607	0.9620	0.8726	**0.9934**
XL4 Macro	0.9219	0.8435	0.9677	0.8990	0.6093	**0.9993**
RTInjection	0.9810	0.7972	0.7915	0.9206	0.4753	**0.9990**

Evasion and Countermeasures

- Macro code detection evasion
  - Good at VBA macro
  - Unstable on XL4 macro
  - Fail to detect remote template injection
    - Document at first attack stage has no macro code
- Unimodal deceptive information detection evasion
  - Replace the regular form of misleading with blurred images
  - Change the wording to persuade users
- DitDetector solves the above problems
  - Exploiting the complementary properties of visual and textual encoders
    - textual encoder focuses on malicioussemantics and can counter text evasion
    - visual encoder learns unusual imageelements for robustness

Discussion

- DitDetector faces real-world challenges
  - ML-based adversarial attack
  - Perform a more comprehensive defense solution at different stages of the attack chain
- Some limitations should be improved
  - Sensitive to the language family
    - Now works well in Indo-European languages
    - Improve the compatibility of the encoder for more languages

Conclusion

- We design and implement DitDetector
  - Detect malicious office documents related to macro malware
  - Counter adversarial samples, e.g., non-macro documents
- We evaluate DitDetector on three datasets
  - Outperform four compared SOTA machine learning methods and five AV engines
- Open Source
  - https://gitee.com/yjasper/dit-detector

Thank you!
Q&A

Jia YAN

yanjia2016@iscas.ac.cn