

B@BEL: Leveraging Email Delivery for Spam Mitigation

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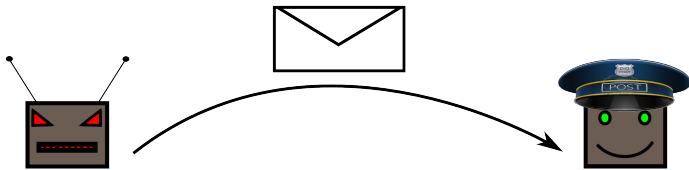
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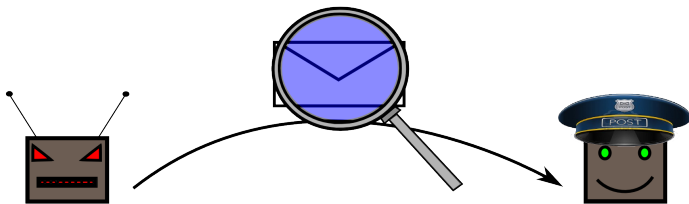
Spam is a big problem

- ▶ Wealthy economy behind spam
- ▶ 77% of emails are spam
- ▶ Botnets responsible for 85% of spam

Traditional spam detection

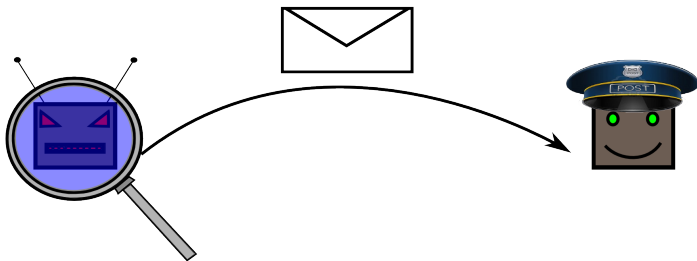


Traditional spam detection



Content analysis (What?)

Traditional spam detection



Origin analysis (Who?)

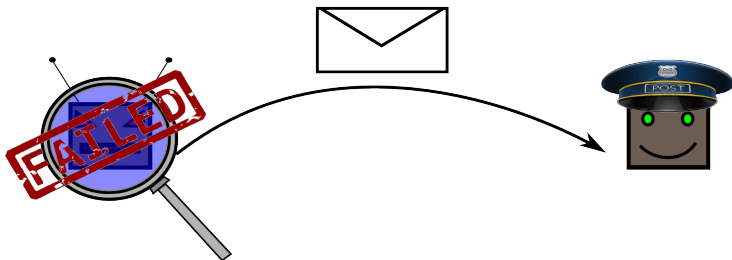
Existing methods have problems



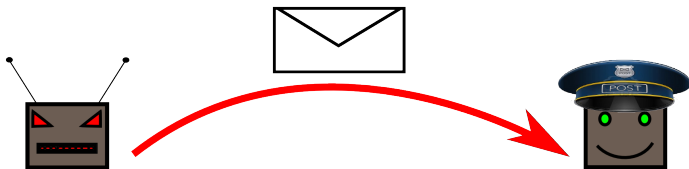
Existing methods have problems



Existing methods have problems



Our approach



The way clients interact with SMTP servers (How?)

Two instances of our approach

- ▶ SMTP dialects
- ▶ Feedback manipulation

Outline of the talk

Techniques overview ←

System design

Evaluation

Limitations

First technique: SMTP dialects

The SMTP protocol

Server: 220 server

Client: HELO example.com

Server: 250 OK

Client: MAIL FROM:<me@example.com>

Server: 250 2.1.0 OK

Client: RCPT TO:<you@example.com>

Server: 250 2.1.5 OK

Client: DATA

*“Be conservative in what you send,
but liberal in what you accept”
(Postel’s Law)*

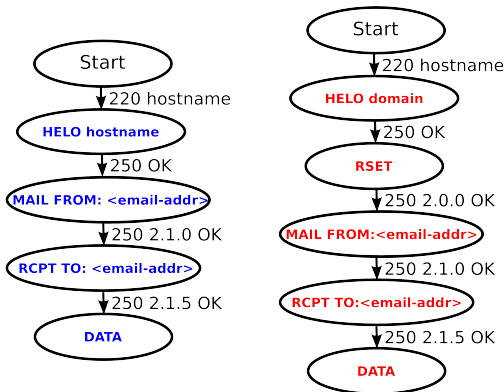
SMTP dialects



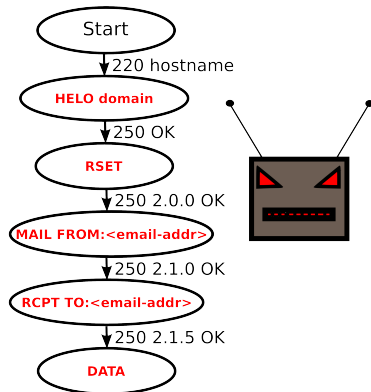
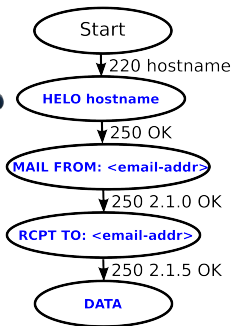
SMTP dialects



SMTP dialects



SMTP dialects



What can we use dialects for?



- ▶ Spam detection
- ▶ Malware classification

Second technique: feedback manipulation

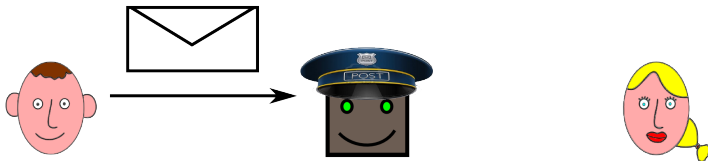
Feedback to emails



Feedback to emails



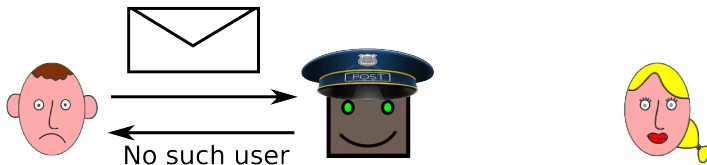
Feedback to emails



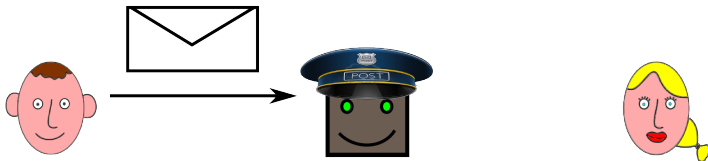
Feedback to emails



Feedback to emails

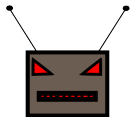


Feedback to emails

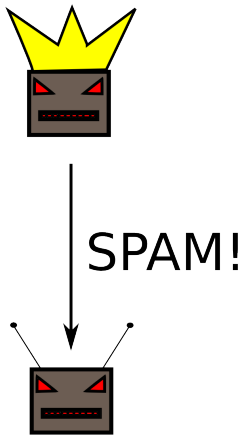


Feedback is important

Botnets use this feedback too



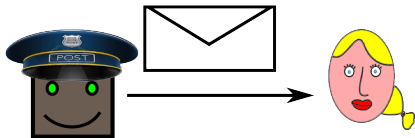
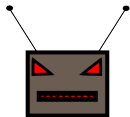
Botnets use this feedback too



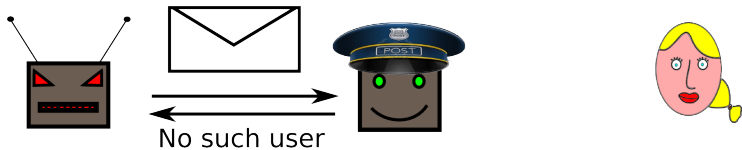
Botnets use this feedback too



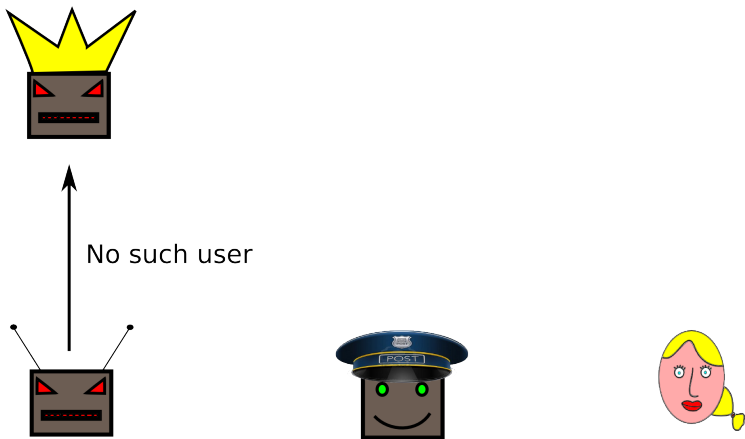
Botnets use this feedback too



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Botnets use this feedback too



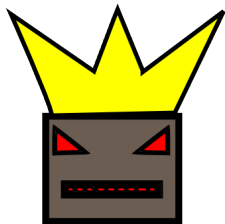
How important is feedback?

Previous research

- ▶ Successful botnets are using bot feedback
- ▶ Cutwail: 35% of the email addresses were nonexistent

What if we gave wrong
feedback?

What should the botmaster do?



Lose-lose situation

- ▶ Accept feedback
- ▶ Discard feedback

Outline of the talk



Techniques overview

System design ←

Evaluation

Limitations

A typical SMTP conversation

Server: 220 server

Client: HELO example.com

Server: 250 OK

Client: MAIL FROM:<me@example.com>

Server: 250 2.1.0 OK

Client: RCPT TO:<you@example.com>

Server: 250 2.1.5 OK

Client: DATA

Dialects as state machines

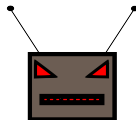
$$\mathbf{D} = \langle \Sigma, S, s_0, T, F_g, F_b \rangle$$

- ▶ Σ : input alphabet
- ▶ S : set of states
- ▶ s_0 : initial state
- ▶ T : transitions
- ▶ F_g : “good” final states
- ▶ F_b : “bad” final states

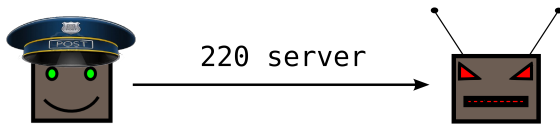
Three phases

- ▶ Learning SMTP dialects
- ▶ Building a decision model
- ▶ Making a decision

Learning SMTP dialects



Learning SMTP dialects



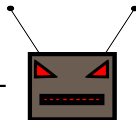
Learning SMTP dialects

S_0

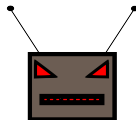
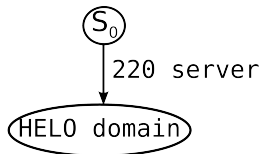
220 server



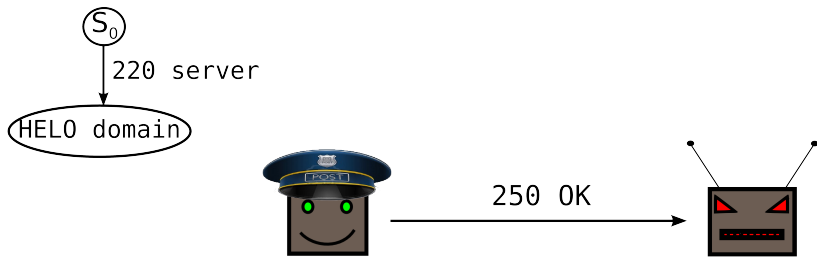
HELO evil.com



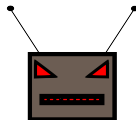
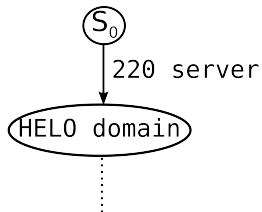
Learning SMTP dialects



Learning SMTP dialects



Learning SMTP dialects



Collecting SMTP conversations

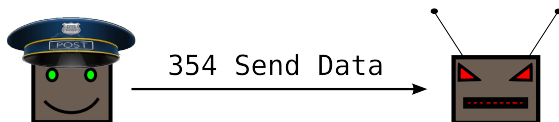
Passive observation

Two dialects might look the same!

Active probing

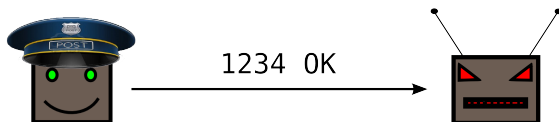
Send incorrect replies, error messages, ...

Active probing



Out-of-order replies

Active probing

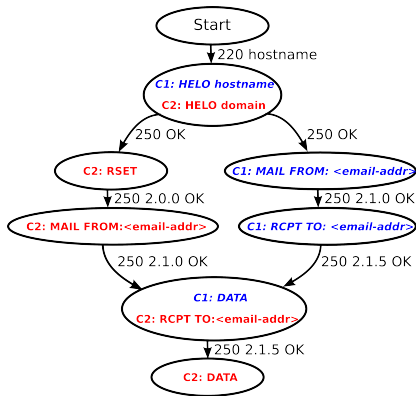


Incorrect replies

Building a decision model



Building a decision model



Making a decision

Passive matching

Detect dialects by observing conversations

Active probing

Send specific replies to “expose” differences

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Dialects for classification

Our experiment

- ▶ 13 legitimate MUAs and MTAs
- ▶ 91 distinct malware samples
- ▶ We performed active probing (228 variations)

Results

- ▶ Legitimate and malicious dialects are distinct
- ▶ Malware families all speak different dialects
- ▶ Better classification than AV labels

Dialects for spam mitigation

Our experiment

621,919 SMTP conversations

Results

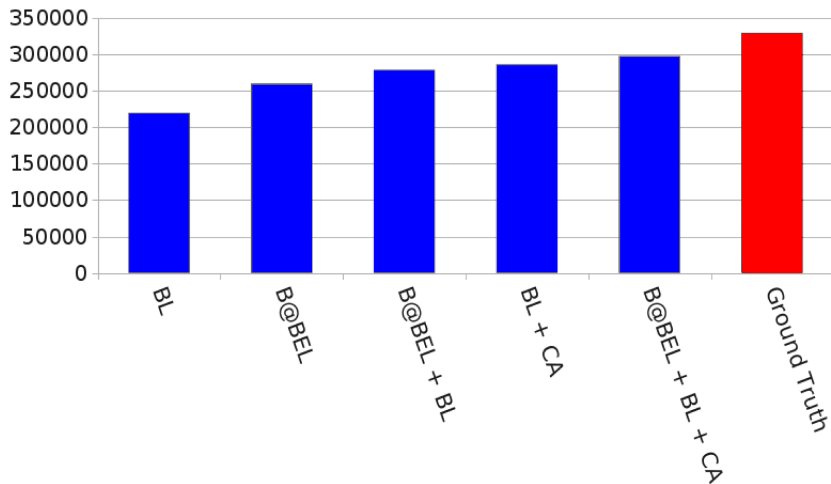
- ▶ 260,074 as bots
- ▶ 218,675 as legitimate clients
- ▶ 143,170 no decision

How accurate is B@BEL?

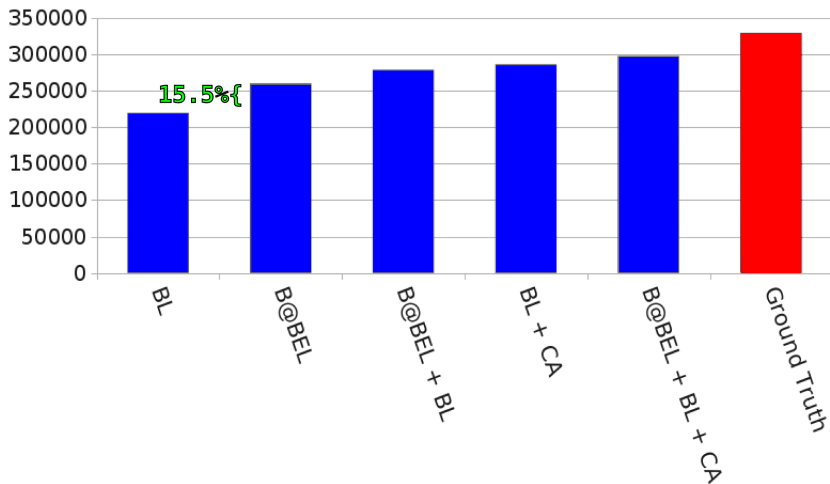
- ▶ 0.67% false positives
- ▶ 21% false negatives

B@BEL detects email engines, not content!

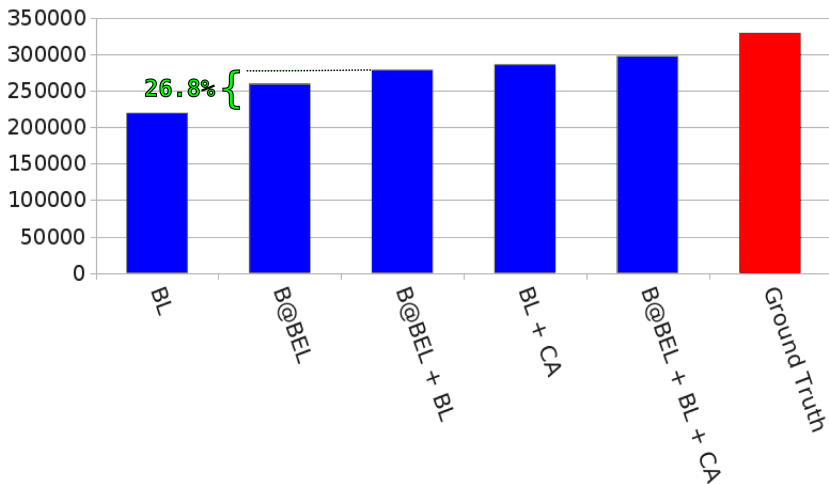
Is it worth it?



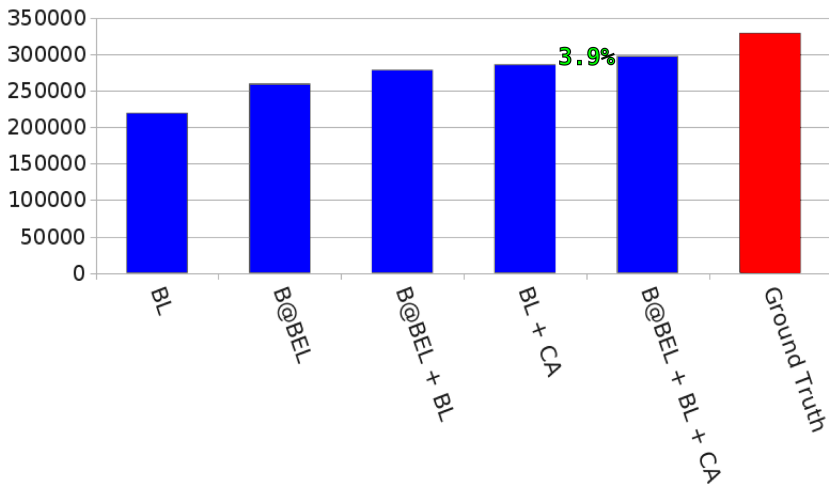
Is it worth it?



Is it worth it?



Is it worth it?

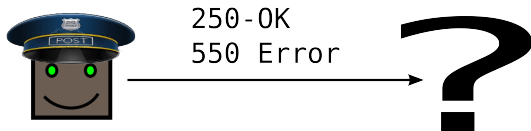


How about those 143,170 emails?



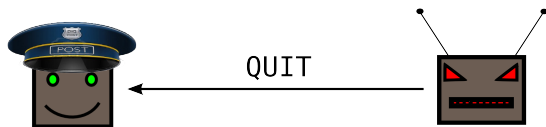
Disambiguation is always possible with one reply

How about those 143,170 emails?



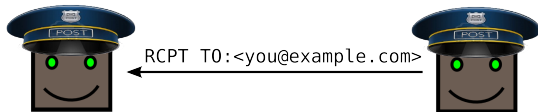
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How about those 143,170 emails?



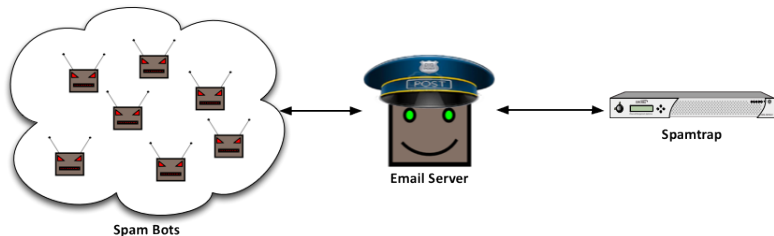
Disambiguation is always possible with one reply

How about those 143,170 emails?



Disambiguation is always possible with one reply

Giving wrong feedback – Evaluation



Our experiment

- ▶ 32 malware samples
- ▶ Sinkholed the emails sent by the bots
- ▶ Looked at the effect on our spam trap

Results

- ▶ Sent feedback to 29 campaigns — 2.8M emails
- ▶ For 5 of them the technique worked
- ▶ 19% of the total number of emails!

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Evading dialects detection

- ▶ Implement a “faithful” SMTP engine

Performance penalty!

- ▶ Force spammers to look like client X

Easier to detect by previous work

Evading feedback manipulation

Lose-lose situation for the botmaster

Conclusions

- ▶ B@BEL looks at how SMTP engines interact with mailservers
 - ▶ SMTP dialects
 - ▶ Feedback manipulation
- ▶ Valuable tool to aid spam mitigation
- ▶ Raises the bar for botmasters

Questions?

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