# Steganographic Key Leakage Through Payload Metadata

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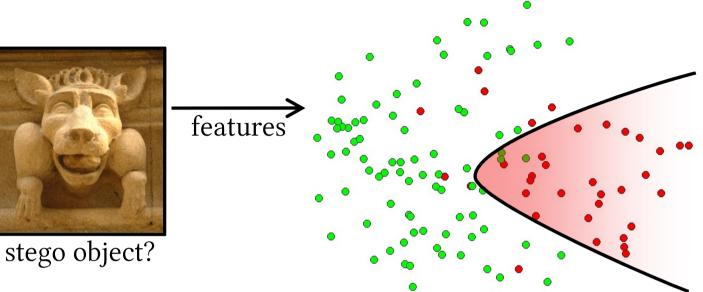






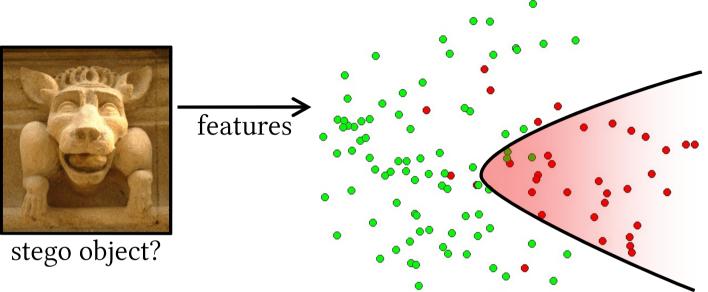
2<sup>nd</sup> ACM Information Hiding Multimedia & Security Workshop Salzburg, 12 June 2014

#### Statistical attacks



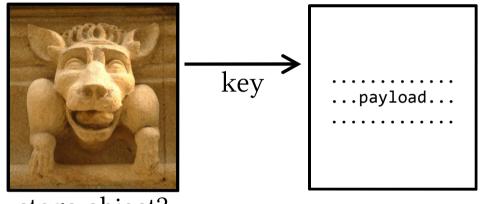
Sophisticated, powerful, but...

### Statistical attacks



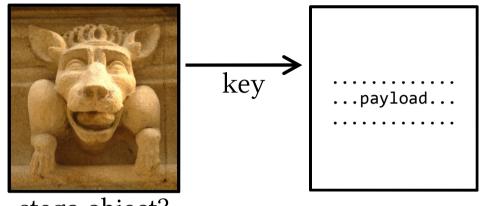
#### Sophisticated, powerful, but...

- Can never give certainty.
- Can never know exactly how accurate it is.



stego object?

Try every key until you recognise a payload.

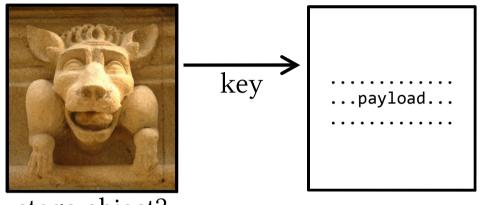


stego object?

<u>**Try every key**</u> until you recognise a payload.

Not feasible if the keyspace is 64 bits, but

- feasible if 32-bit keyspace, or maps into 32-bit space, or
- feasible if keys derived from passwords.

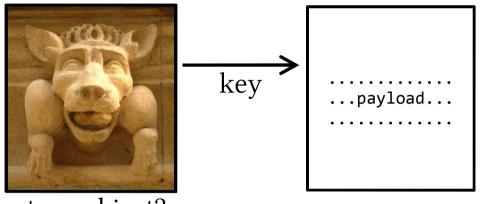


stego object?

Try every key until you **recognise a payload**.

Making payload unrecognisable is difficult:

- use unstructured plaintext?
- encrypt with second password?



stego object?

#### Assumptions

- Keyspace exhaustible.
- Plaintext unrecognisable.

Seek statistical evidence that one key is more likely, or a short list of keys for a second attack on the plaintext.

# **Related work**

#### Assumptions

- Keyspace exhaustible.
- Plaintext unrecognisable.

Provos [2001] For each key, check consistency of OutGuess 'header block'.

Fridrich et al. [2004], Böhme et al. [2012] For each key, compare statistics of used vs. unused locations.

Ker [2007], Quach [2011+]

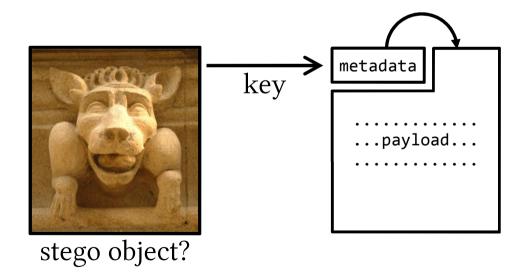
Look for correlated residuals between different stego images.

# Model

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- Plaintext unrecognisable.
- Multiple stego objects embedded with same key.

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- Plaintext unrecognisable.
- Multiple stego objects embedded with same key.
- Payload decoded via metadata:



# Payload metadata

Most implementations use metadata:

- Payload size (to know when to stop decoding).
- Hamming code parameters.
- Syndrome Trellis Code parameters.
- ...

For each stego image,

for each key,

decode metadata & discard impossible keys.

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#### Example

- OutGuess
- Uniformly random message length
- Keyspace: 2 million passwords
- Metadata = message length
- Discard length > capacity
- Experiment repeated 1000 times

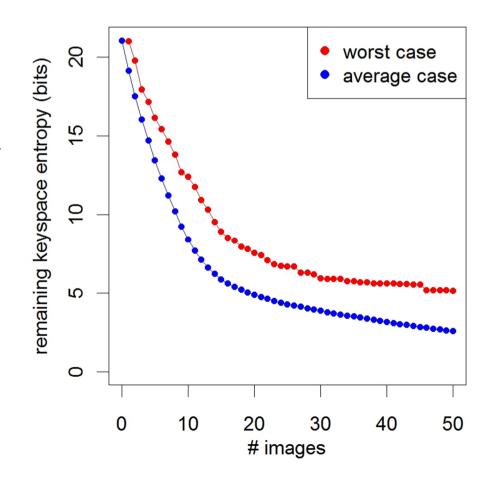
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e.g. code parameter = metadata (mod maximum)

# Quantitative steganalysis

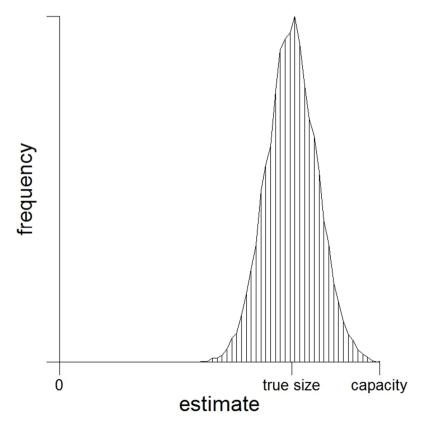
Attacking the embedding, can often estimate the length of payload in a stego image:

- old-fashioned 'structural steganalysis',
- support vector regression based on features, etc.

# Quantitative steganalysis

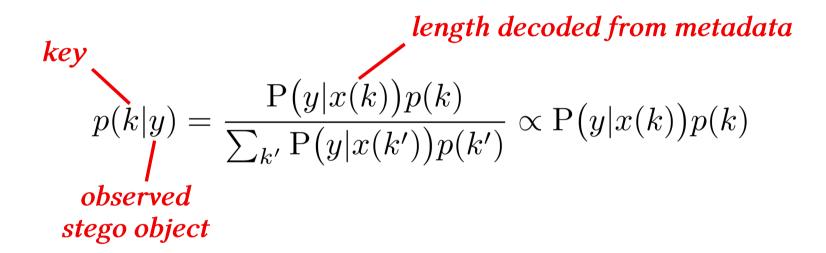
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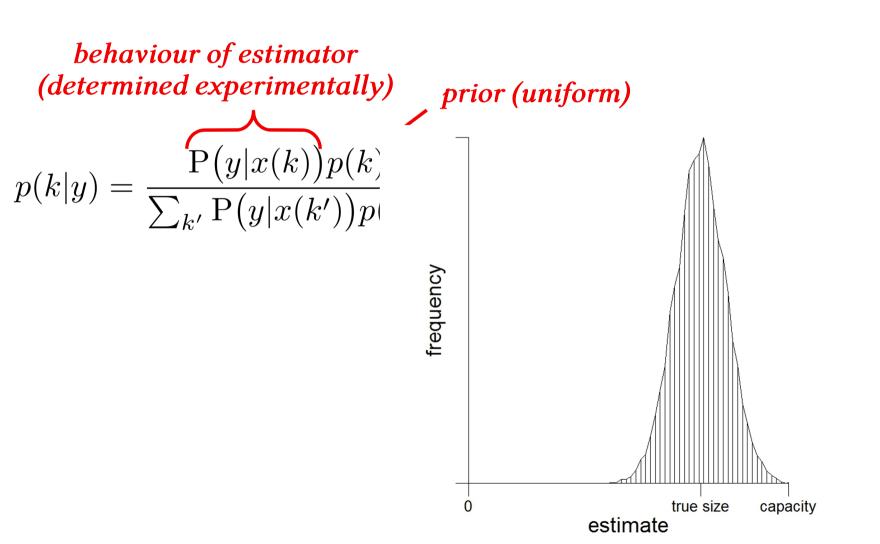
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decode metadata & compute score

$$\log p(k|y_1,\ldots,y_n) = \log p(k) + \sum_{i=1}^n \log P(y_i|x(k))$$

 $\mathbf{n}$ 

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# images

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#### Examp

- OutG
- Unifor
- Keysp
- Metad
- PF-548
- Exper

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#### Countermeasure?

Key inference has 'exponential power': extracted metadata is **independent** across images (if the key is incorrect).

Try to make it **dependent**, as for correct keys?

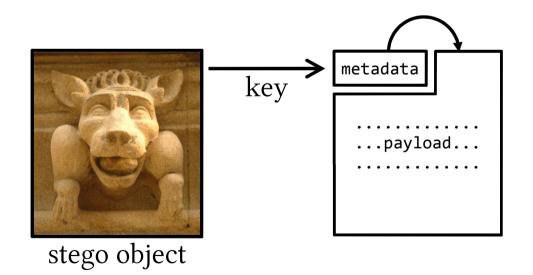
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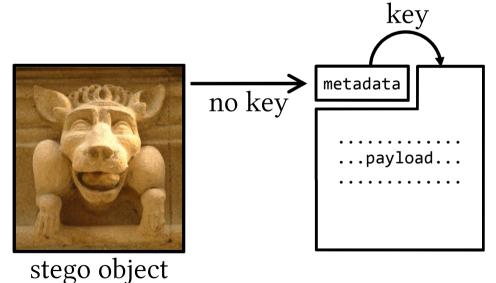
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e.g. length = (metadata + key) (mod capacity) and the metadata is stored at a fixed location

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 $\mathbf{n}$ 

#### Countermeasure?

- Simulated 16-bit payload size
- Uniformly random message length
- length = (metadata + key) (mod capacity)
- PF-548 features  $\rightarrow$  length estimate
- Repeated 1000 times

For each key,

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features  $\rightarrow$  length estimate
  
ated 1000 times
  
 $p = \frac{1}{p}$ 
  
 $p =$ 

0

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# images

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#### Counter

- Simula
- Unifor:
- lengtl ullet
- PF-548
- Repeat

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$$\log p(k|y_1,\ldots,y_n) = \log p(k) + \sum_{i=1}^n \log P(y_i|x(k))$$

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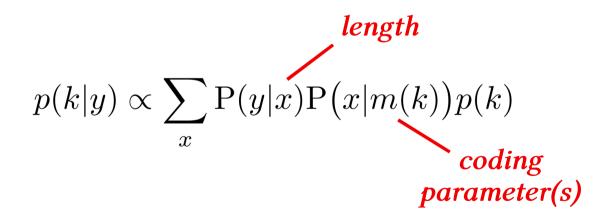
However, this introduces new statistical attacks.

If the metadata does not determine payload length, it probably gives information about it:

- Optimal Hamming code size determined by relative payload.
- STC width closely related to inverse payload.

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probably uniform between certain limits

 $p(k|y) \propto \sum_{x} \mathbf{P}(y|x) \mathbf{P}(x|m(k)) p(k)$ coding parameter(s)

For each key,

decode metadata & compute score  $\boldsymbol{n}$ 

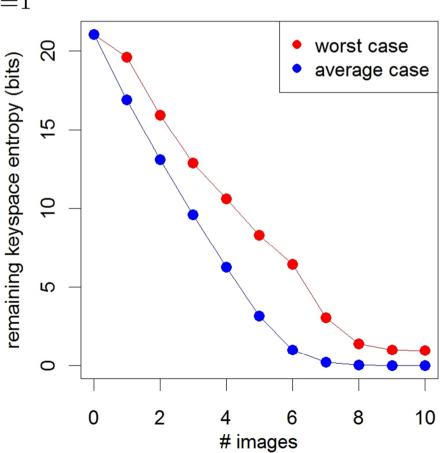
$$\log p(k|y_1, \dots, y_n) = \log p(k) + \sum_{i=1}^n \log \sum_x P(y_i|x) P(x|m(k))$$
**Example**
• OutGuess
$$\widehat{g_i} = \widehat{g_i} + \widehat{g$$

- Keyspace: 2 million passwords •
- Hamming  $[2^p, 2^p p 1]$  code •
- Metadata = p•

()

•

- PF-548 features  $\rightarrow$  length estimate •
- Repeated 1000 times •



Presented ways to improve exhaustion attacks through statistical steganalysis evidence.

We are attacking implementation weaknesses, not steganographic weaknesses.

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We are attacking implementation weaknesses, not steganographic weaknesses.

Implementations can avoid all these attacks if:

- their keyspace is not exhaustible, or
- keys are never reused, or
- no metadata is stored...

... but such mistakes are plausible and common.

If keys must be re-used, we have to make hard choices:

Embed metadata

Do not embed metadata

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Security against statistical attacks

Security against exhaustion attacks

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Store metadata cryptographically Do not embed metadata

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