The Ultimate Steganalysis Benchmark?



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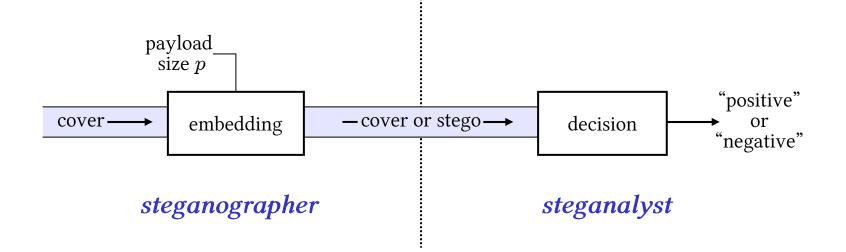
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The Ultimate Steganalysis Benchmark?

Outline

- Currently-used benchmarks not ideal
- New benchmark based on KL divergence
- Difficulties estimating the benchmark value
- Examples

Binary Steganalysis



Common Benchmarks

• ROC curve

difficult to rank; too much information

- Area under ROC
- Minimize sum of false positive & negative assumes false positive and false negatives are equivalent
- False negative rate at fixed false positive
- False positive rate at fixed false negative *impossible to justify numbers objectively*

Common Benchmarks

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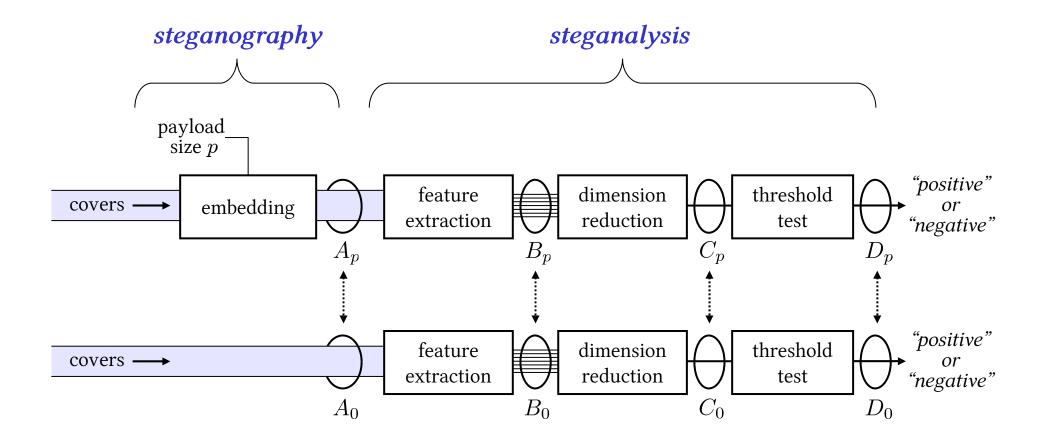
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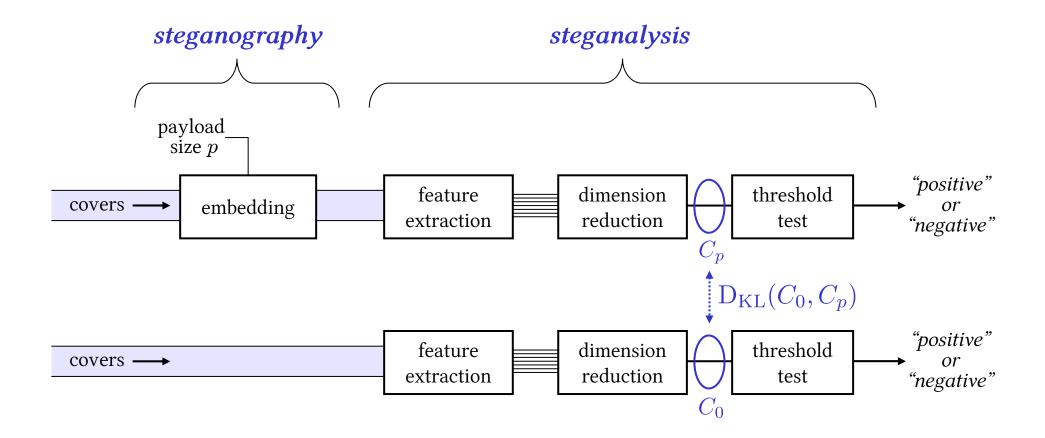
also depend on payload size

• Minimum payload detectable at fixed false positive & false negative rate *impossible to justify numbers objectively*

Distribution Differences



Distribution Differences



New Benchmark

- Based on $D_{KL}(C_0, C_p)$, where C_p is the univariate distribution produced just before threshold test.

From steganalysis/info theory literature

If steganography is repeated at a fixed embedding rate, the probability of detection tends to 1. [Cachin; Moulin; Ker; ...]

• For long-run performance we should concentrate on payload sizes tending to zero.

A theorem by S. Kullback

Let F_p be a family of distributions satisfying certain regularity conditions. Then $\lim_{p\to 0} \frac{D_{KL}(F_0, F_p)}{p^2}$ exists and is nonzero. [adapted from Kullback, 1968]

• If we believe that the regularity conditions are satisfied, then $D_{KL}(C_0, C_p)$ is, locally to zero, a multiple of p^2 .

New Benchmark

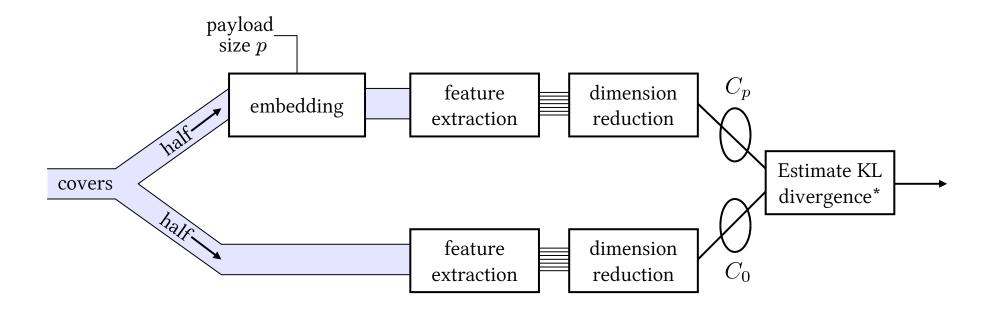
The quantity $Q = \lim_{p \to 0} \frac{\mathcal{D}_{\mathrm{KL}}(C_0, C_p)}{p^2}$

tells us how quickly "evidence" accumulates. This is the proposed benchmark.

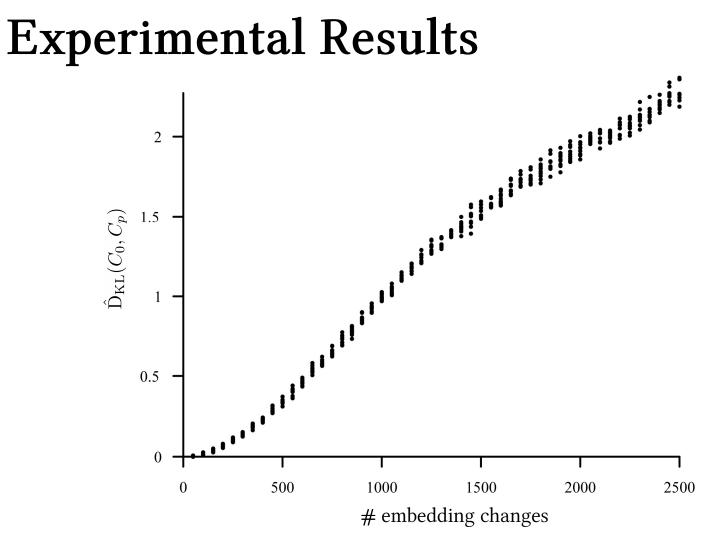
Note:

- "Payload size" should be measured by number of embedding changes
- Then Q is measured in "nats per embedding change squared"

Experimental Results

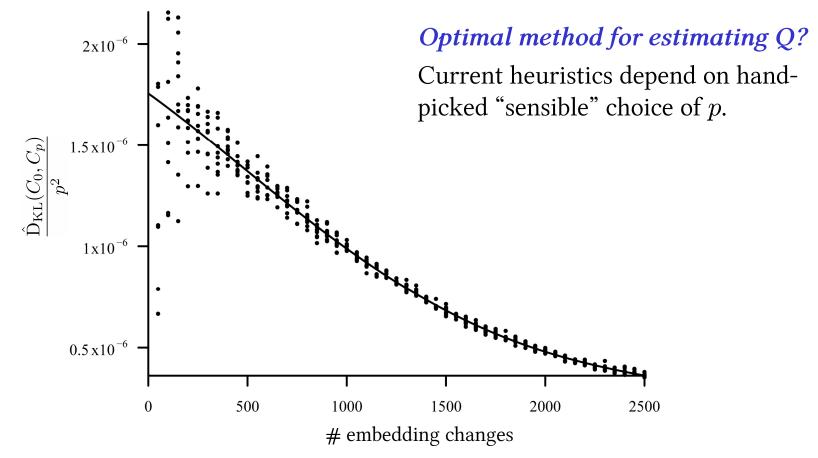


*KL divergence estimation by [Wang, Kulkarni, & Verdu, 2005]



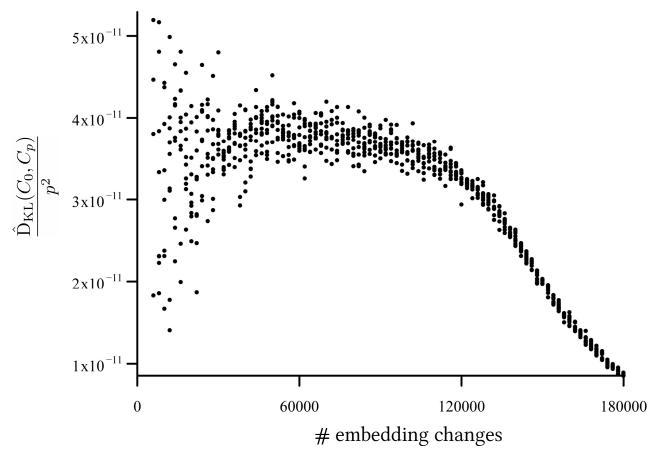
- 10000 cover images
- LSB replacement embedding, 50 payload sizes, repeated 10 times each
- "Triples" steganalysis

Experimental Results



- 10000 cover images
- LSB replacement embedding, 50 payload sizes, repeated 10 times each
- "Triples" steganalysis

Experimental Results



- 20000 cover images
- LSB matching (±1) embedding, 90 payload sizes, repeated 10 times each
- "Calibrated HCF COM" steganalysis

Conclusions

- There is a need for an application-independent benchmark.
- The new "Q-factor" benchmark measures how quickly **information** is accumulated as payload increases.
- More work needed for good empirical estimation of "Q":
 - Currently seems to need a very large experimental base
 - Test objects should be the same size
 - Optimal estimation?

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- There is a need for an application-independent benchmark.
- The new "Q-factor" benchmark measures how quickly **information** is accumulated as payload increases.
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Steganalysis	3000 grayscale bitmap covers	10000 colour JPEG covers
SPA [Dumitrescu et al, IHW 2002]	16.1	28.3
SPA/LSM [Lu et al, IHW 2004]	12.1	161
Triples [Ker, IHW 2005]	20.7	1500
Triples/WLSM [Ker, SPIE EI 2007]	16.1	1500

nanonats per embedding change squared

End

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