# Detection of Content Adaptive LSB Matching (a Game Theory Approach)

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#### **Content-adaptive steganography**

• Every pixel is changed with probability

$$\beta_i = \frac{\exp(-\lambda\rho_i)}{1 + \exp(-\lambda\rho_i)},$$

where  $\rho_i \ge 0$  are costs for each pixel and  $\lambda$  determined from the payload constrain  $\frac{1}{n} \sum_{i=1}^{n} h(\beta_i) = \alpha$ .

- Costs determined by image content  $\implies$  approximately available to Warden who can adjust detector accordingly.
- How does this change Alice's embedding strategy?

### Two fundamental approaches

Omnipotent Warden [Cachin, 1998]
Warden knows payload and embedding probabilities for each pixel.
Alice minimizes KL divergence between cover/stego distributions.

 Ignorant Warden [Böhme, 2012] Warden knows only the payload. Alice can embed suboptimally (not minimize KL-div) to utilize mismatch of Warden's detector.

Our contribution

- We investigate modern steganography (LSBM).
- Warden uses LRT for detection.



#### Notation

Gaussian density with mean  $\mu$  and variance  $\sigma^2$ :

$$f(x;\mu,\sigma^2) = (2\pi\sigma^2)^{-1/2} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right),$$

 $\{-1,0,1\}\text{-mixture of Gaussian densities with a parameter <math display="inline">0\leq\beta\leq1/2\text{:}$ 

$$f_{\beta}(x;\sigma^2) = \frac{\beta}{2}f(x;-1,\sigma^2) + (1-\beta)f(x;0,\sigma^2) + \frac{\beta}{2}f(x;1,\sigma^2).$$

### **Cover Model**

We assume cover is a sequence of n independent Gaussians  $X_i$  with unequal variances  $\sigma_i^2$ :

$$\mathbf{X} = (X_1, \dots, X_n), \quad X_i \sim N(0, \sigma_i^2), \quad i = 1, \dots, n.$$

# **Embedding Method**

- Alice uses LSBM with change rates  $\beta_i^{(A)}$ ,  $i = 1, \ldots, n$ .
- Stego image  $\mathbf{Y} = (Y_1, \ldots, Y_n)$ ,

$$\Pr(Y_i = x_i + s_i) = \begin{cases} \beta_i^{(A)}/2 & \text{ for } s_i = -1, \\ 1 - \beta_i^{(A)} & \text{ for } s_i = 0, \\ \beta_i^{(A)}/2 & \text{ for } s_i = 1. \end{cases}$$

Therefore

$$Y_i \sim f_{\beta_i^{(A)}}(x, \sigma_i^2)$$

• Change rates must satisfy payload constraint

$$\sum_{i=1}^{n} h(\beta_i^{(\mathbf{A})}) = \alpha n$$

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#### Warden's Detector

• Simple binary hypothesis test:

$$\begin{aligned} \mathbf{H}_0: \ X_i &\sim f(x, 0, \sigma_i^2), \ \forall i, \\ \mathbf{H}_1: \ X_i &\sim f_{\beta_i^{(\mathrm{W})}}(x, \sigma_i^2), \ \forall i, \end{aligned}$$

 $\beta_i^{(\mathrm{W})}$  are change rates assumed by Warden

• Warden uses the Likelihood Ratio Test (LRT):

$$T(\mathbf{x};\boldsymbol{\beta}^{(\mathrm{W})},\boldsymbol{\sigma}^2) = \prod_{i=1}^n \frac{f_{\beta_i^{(\mathrm{W})}}(x_i,\sigma_i^2)}{f(x_i,0,\sigma_i^2)}$$

$$oldsymbol{eta}^{(\mathrm{W})}=(eta_1^{(\mathrm{W})},\ldots,eta_n^{(\mathrm{W})})$$
 and  $oldsymbol{\sigma}^2=(\sigma_1^2,\ldots,\sigma_n^2)$ 

# Alice and Warden Play Game

- Players: Alice and Warden
- Strategies:  $\beta^{(A)} = (\beta_1^{(A)}, \dots, \beta_n^{(A)})$  and  $\beta^{(W)} = (\beta_1^{(W)}, \dots, \beta_n^{(W)})$
- Payoff function: total error probability

$$P_{\rm E} = \min_{P_{\rm FA}} \left( \frac{1}{2} (P_{\rm FA} + P_{\rm MD}) \right)$$

• The game solution is in Nash equilibrium.

# **Two Pixel Model**

- Because of the computational and numerical complexity we limit ourselves to covers consisting of two pixels.
- Strategies:  $(\beta_1^{(A)}, \beta_2^{(A)})$ ,  $(\beta_1^{(W)}, \beta_2^{(W)})$  are in fact one-dimensional since the second beta is determined from payload.
- $\bullet$  [Omnipotent Warden] KL divergence minimal at  $(\beta_1^{(\mathrm{A},1)},\beta_2^{(\mathrm{A},1)})$
- [Ignorant Warden] Nash equilibrium at  $(\beta_1^{(\mathrm{A},2)},\beta_2^{(\mathrm{A},2)})$

#### Solution

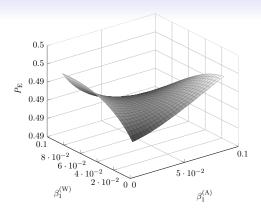


Figure: Payoff function  $P_{\rm E}(\beta_1^{\rm (A)}, \beta_1^{\rm (W)})$  for  $\alpha = 0.2$ ,  $\sigma_1^2 = 1$ ,  $\sigma_2^2 = 1.2$ .

Smooth, with a unique saddle point  $\Rightarrow$  [Kuhn, 2003] solution exists in pure strategies, in said saddle point.



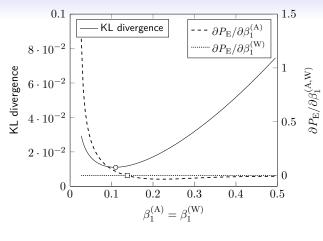


Figure:  $\alpha = 0.2$ ,  $\sigma_1^2 = 1$ ,  $\sigma_2^2 = 1.2$ .



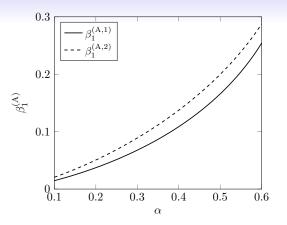


Figure: Alice's strategies under both scenarios  $\beta_1^{(A,1)}$ ,  $\beta_1^{(A,2)}$  as a function of  $\alpha$  for  $\sigma_1^2 = 1$  and  $\sigma_2^2 = 1.2$ .



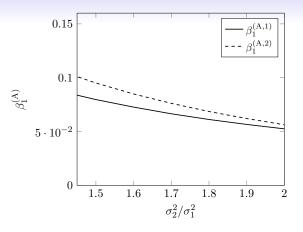


Figure: Alice's strategies under both scenarios  $\beta_1^{(A,1)}$ ,  $\beta_1^{(A,2)}$  as a function of content diversity measured by the ratio  $\sigma_2^2/\sigma_1^2$  for  $\alpha = 0.4$  and  $\sigma_1^2 = 1$ .





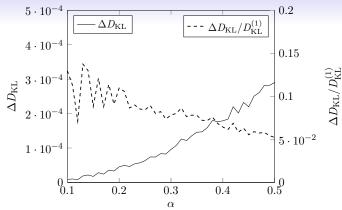


Figure: Warden's loss in her ability to detect Alice's embedding,  $\triangle D_{\rm KL}(\ln T | {\rm H_0} || \ln T | {\rm H_1})$  and  $\triangle D_{\rm KL} / D_{\rm KL}^{(1)}$ , as a function of  $\alpha$  for  $\sigma_1^2 = 1$  and  $\sigma_2^2 = 1.2$ .



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# Summary

- In practice Warden rarely has full access to the steganographic channel.
- Even the simplistic two pixel cover source reveals interesting phenomena:
  - Nash equilibrium  $\neq$  point of minimal KL divergence.
  - It pays off for Alice to trade optimality for a mismatched detector.
- It is always advantageous for Alice to embed a slightly larger payload into the element with a smaller variance.
  - The difference between optimal strategies increases with increasing  $\alpha.$
  - The difference between optimal strategies decreases with increasing differences between  $\sigma_1^2$  and  $\sigma_2^2.$
- Computational complexity and numerical issues prevent scaling up this approach to realistic covers.