

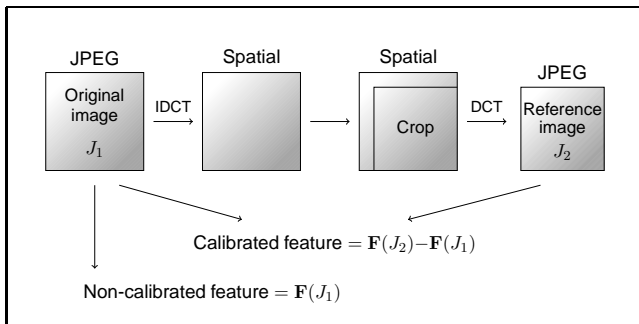
Calibration Revisited

Jan Kodovský, Jessica Fridrich

September 7, 2009 / ACM MM&Sec '09

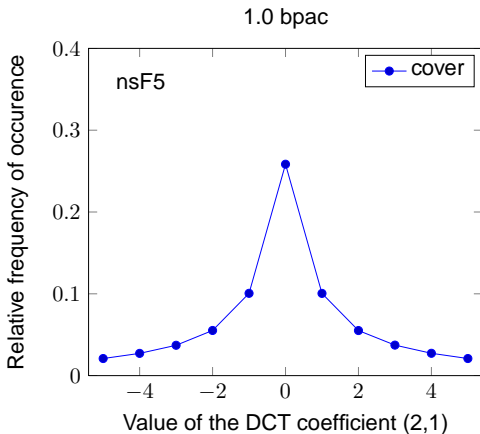
What is Calibration?

- 2002 - Calibration introduced (attack on F5)
- Part of feature extraction procedure for blind steganalysis
- Idea: estimate cover image statistics from the stego image



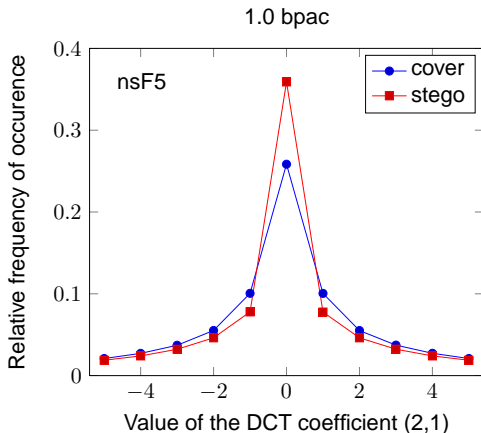
Motivation

- How well does calibration approximate cover?
- Experiment: local histograms (average over 6,500 images)



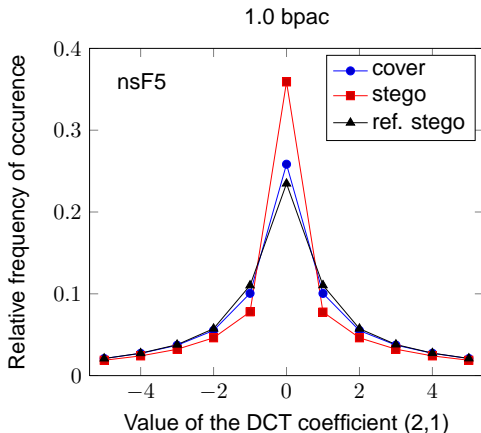
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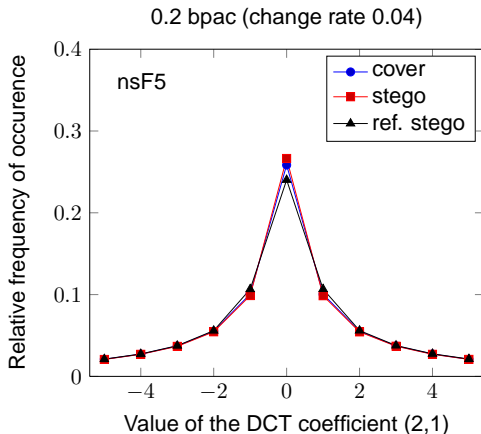
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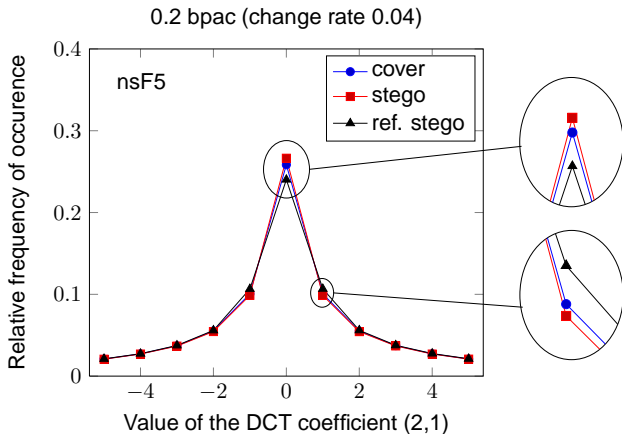
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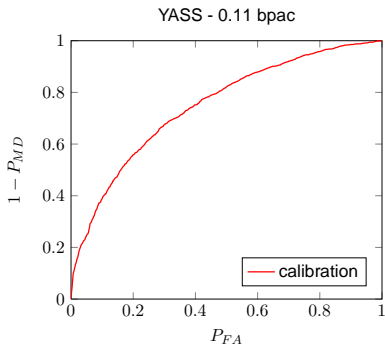
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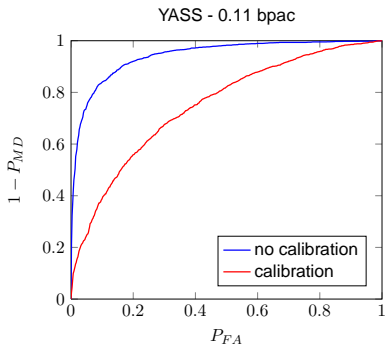
Motivation, cont'd

- Detectability of the steganographic algorithm YASS
- [Pevný 2007] - 274 merged features (Pevný Feature Set)
- SVM machine with Gaussian kernel, 6500 images



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Challenges

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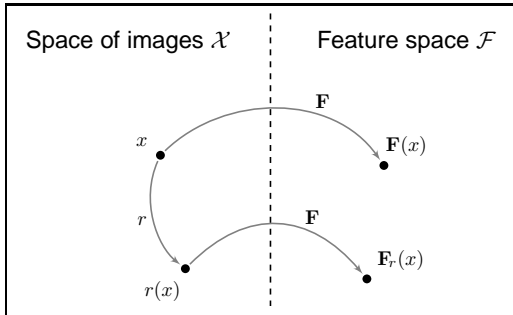
- How exactly does calibration affect detectability of steganographic algorithms?
- What is the real purpose of calibration?
- Does it make sense to calibrate all features?

Goals

- Create appropriate model for calibration
- Quantitative evaluation of the contribution of calibration to steganalysis performance

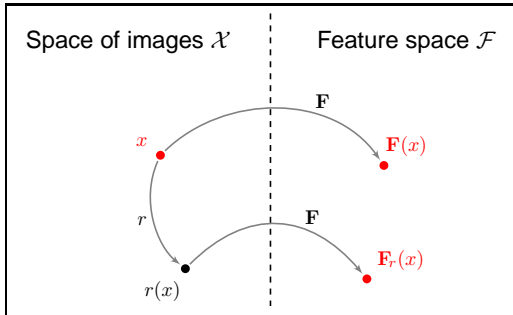
Notation

- Feature mapping ... $\mathbf{F} : \mathcal{X} \rightarrow \mathcal{F}$
- Reference transform ... $r : \mathcal{X} \rightarrow \mathcal{X}$
- Reference-feature mapping ... $\mathbf{F}_r = \mathbf{F} \circ r : \mathcal{X} \rightarrow \mathcal{F}$

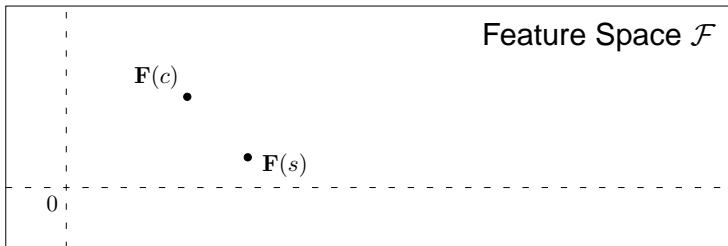


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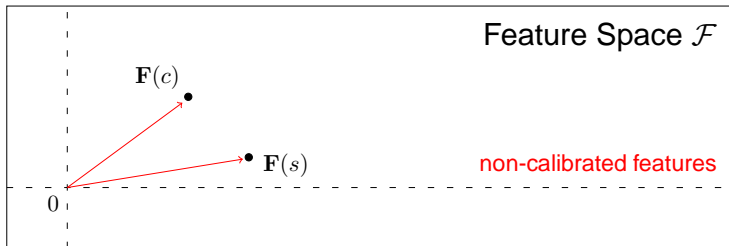
Basic Concept



$\mathbf{F}(c), \mathbf{F}(s) \dots$ original features

$\mathbf{F}_r(c), \mathbf{F}_r(s) \dots$ reference features

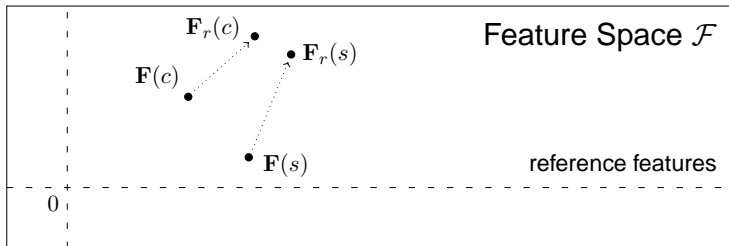
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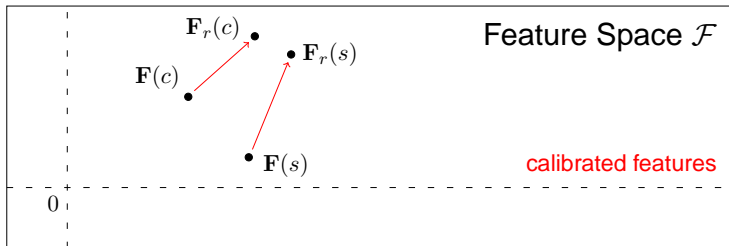
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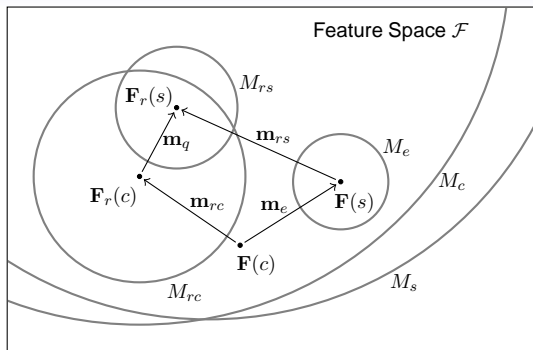
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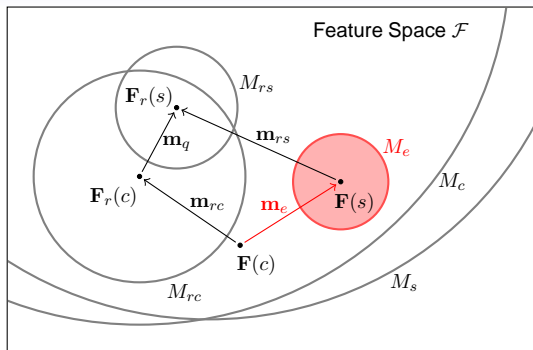
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Proposed Model



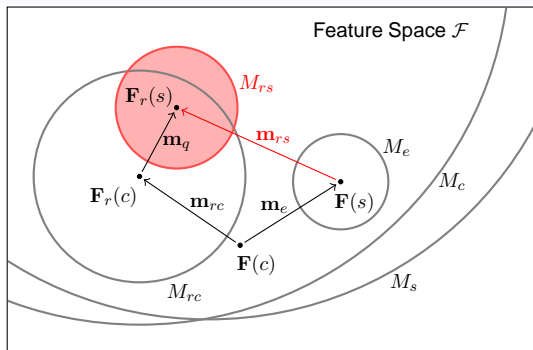
Proposed Model



$$\mathbf{m}_e = \text{median} [\mathbf{F}(s) - \mathbf{F}(c)],$$

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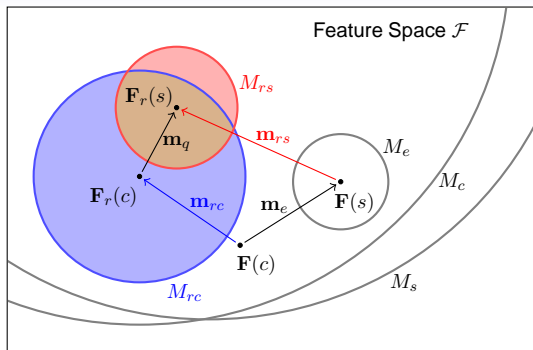
Proposed Model



$$\mathbf{m}_{rs} = \text{median} [\mathbf{F}(rs) - \mathbf{F}(s)],$$

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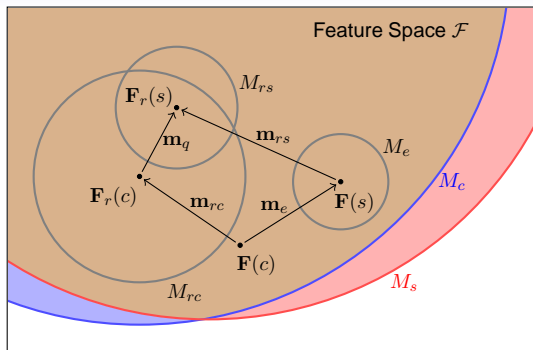
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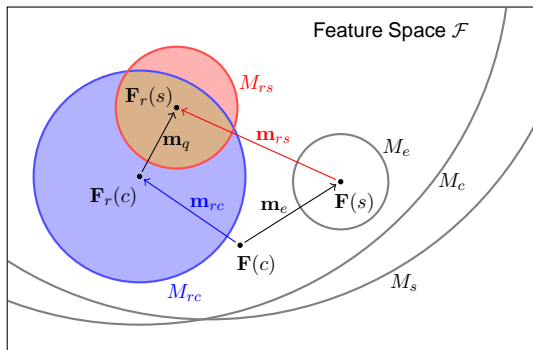
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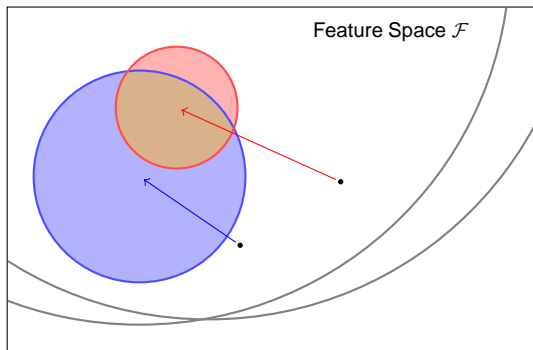
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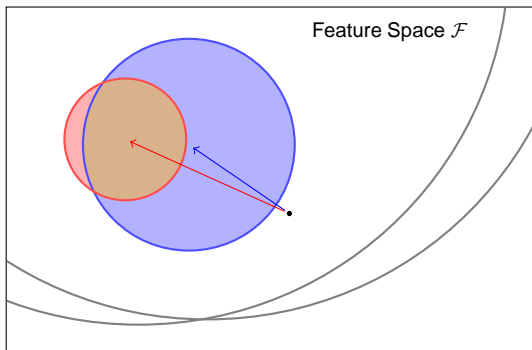
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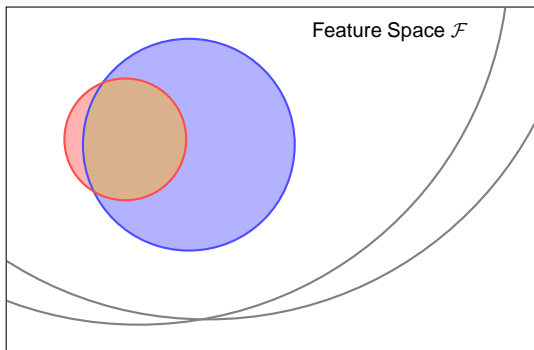
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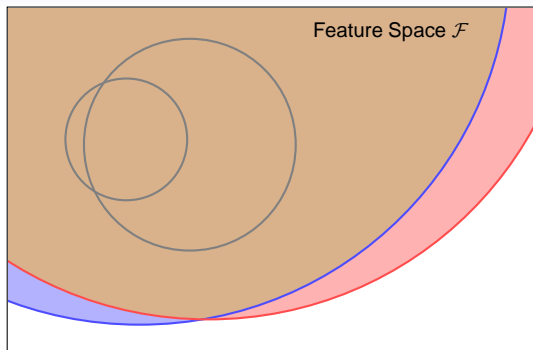
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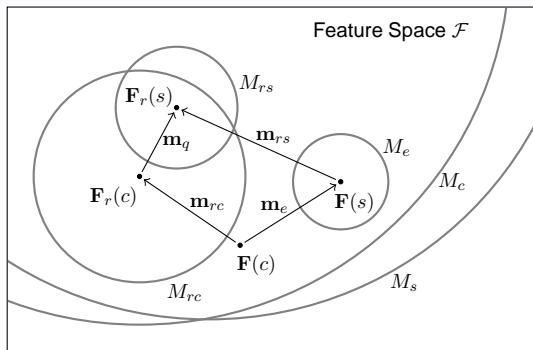
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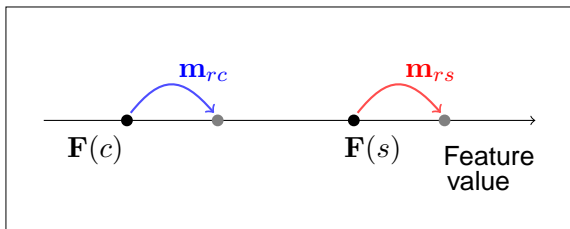


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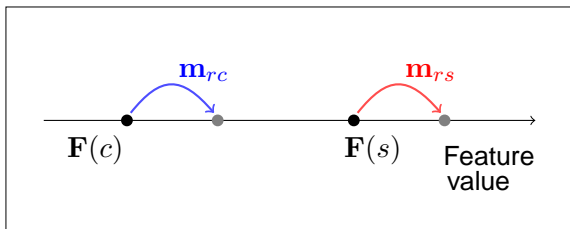
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- $\mathbf{m}_{rc} \approx \mathbf{m}_{rs}$, $M_{rc} \approx M_{rs}$
- Calibration can be seen as a constant feature-space shift
- Calibration causes failure of steganalysis



Parallel Reference

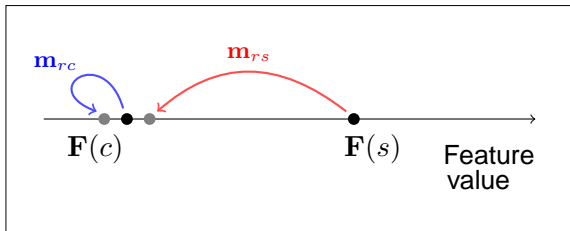
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- Experiments: observed often for YASS (robustness!)

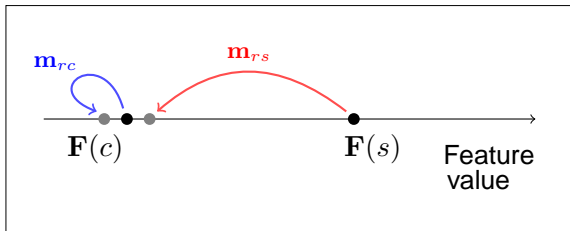
Cover Estimate

- Both m_{rc} and m_{rs} are close to cover feature $F(c)$
- This stood behind the original idea of calibration
- Stego-image feature must differ from cover-image feature



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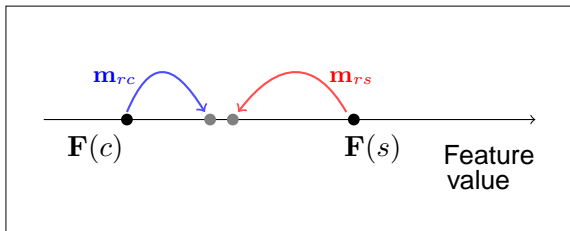
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- Experiments: easier to observe for larger payloads

Eraser

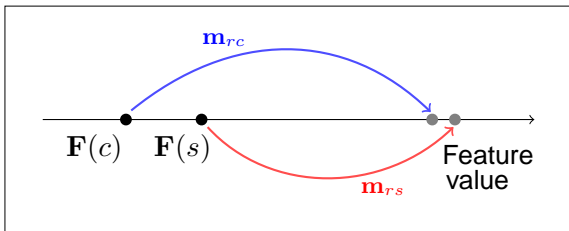
- Reference cover and stego features are close to each other
- Mapping r erases embedding changes
- $F(c) \rightarrow F(s)$ must be consistent in terms of direction



- Experiments: more frequent than cover estimate

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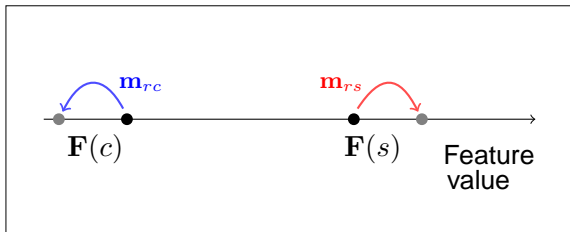
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- Experiments: more frequent than cover estimate
- Different example: predictor in WS steganalysis

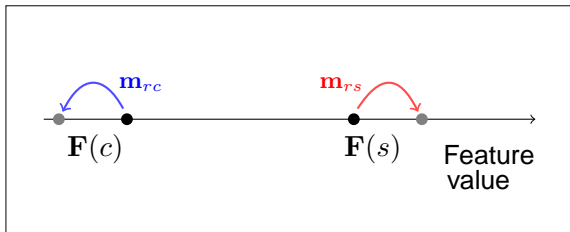
Divergent Reference

- m_{rc} must be different from m_{rs}
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- Experiments: most frequent scenario
- Interesting example: histogram of zeros for JSteg

Lessons Learned

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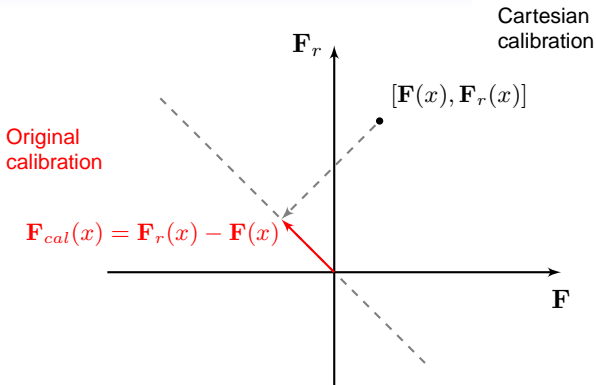
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- Calibration may have a catastrophically negative effect on steganalysis as well (parallel reference).

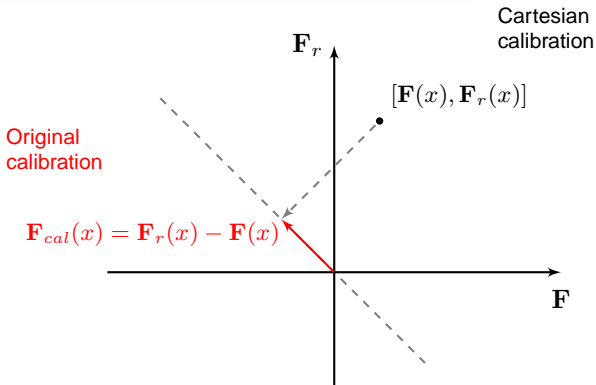
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- How to prevent steganalysis from such failures?

Different Point of View



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How well does Cartesian calibration perform in practice?

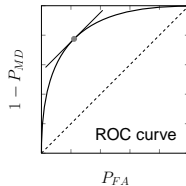
Cartesian Calibration Improves Steganalysis

Algorithm	bpac	P_E		
		F	$F_r - F$	$[F_r, F]$
nsF5	0.05	0.361	0.360	0.331
	0.10	0.202	0.218	0.177
	0.15	0.100	0.094	0.077
	0.20	0.048	0.040	0.036
Jsteg	0.02	0.097	0.132	0.083
	0.03	0.042	0.051	0.032
	0.04	0.022	0.021	0.018
Steghide	0.05	0.015	0.013	0.010
	0.02	0.114	0.127	0.083
	0.03	0.055	0.056	0.043
	0.04	0.031	0.031	0.024
MME3	0.05	0.021	0.015	0.011
	0.05	0.309	0.310	0.277
	0.10	0.187	0.207	0.165
	0.15	0.130	0.149	0.107
	0.20	0.023	0.017	0.012

Algorithm	bpac	P_E		
		F	$F_r - F$	$[F_r, F]$
JPHS	0.05	0.306	0.100	0.094
	0.10	0.160	0.066	0.054
	0.15	0.076	0.034	0.022
	0.20	0.039	0.014	0.006
	YASS 1	0.110	0.133	0.317
YASS 2	0.051	0.179	0.347	0.164
YASS 3	0.187	0.102	0.121	0.082
YASS 4	0.118	0.120	0.303	0.109
YASS 5	0.159	0.075	0.241	0.064
YASS 6	0.032	0.269	0.342	0.258
YASS 7	0.078	0.244	0.298	0.225
YASS 8	0.138	0.211	0.251	0.180

Reported values of P_E are medians over 5 runs.

$$P_E = \min \frac{1}{2} (P_{FA} + P_{MD})$$



Calibration Revisited

- Shed more light on how, why, and when calibration works
- Introduced a new framework capable of both quantitatively and qualitatively capture behaviour of calibration in the feature space
- Supported our findings experimentally
- Proposed an improved way of calibration
 - Extractor of Cartesian-calibrated 274 merged features available

<http://dde.binghamton.edu/ccmerged>