

# Attacks on Online Handwriting Biometrics

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# Motivation

Data becoming more portable (PDA's, cell phones, laptops, etc.) – theft is a growing concern.

Why aren't passwords enough?

- Very easy to “crack.”
- Thief can disassemble and reverse-engineer device.

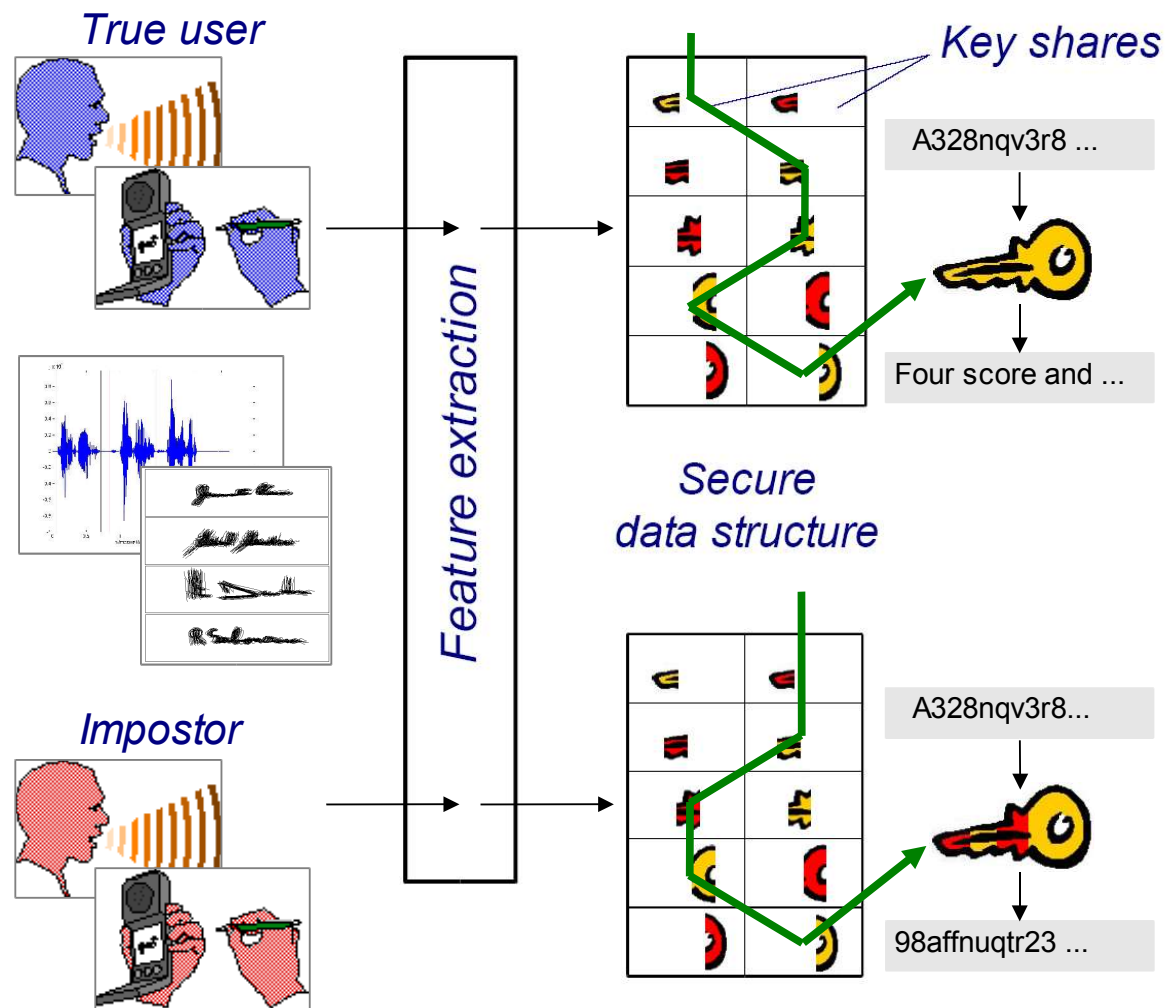


Two-pronged solution:

- Biometrics in place of (or in addition to) passwords.
- Secure data structure to encrypt information.

# Using Biometrics to Protect Data

- Cryptographic key broken into shares and mixed with random data.
- Features extracted from user's speech or handwriting.
- Only input from true user selects shares to yield key.



“Towards Speech-Generated Cryptographic Keys on Resource-Constrained Devices,” F. Monrose, M. Reiter, Q. Li, D. Lopresti, and C. Shih, *Proceedings of the Eleventh USENIX Security Symposium*, August 2002, San Francisco, CA, pp. 283-296.

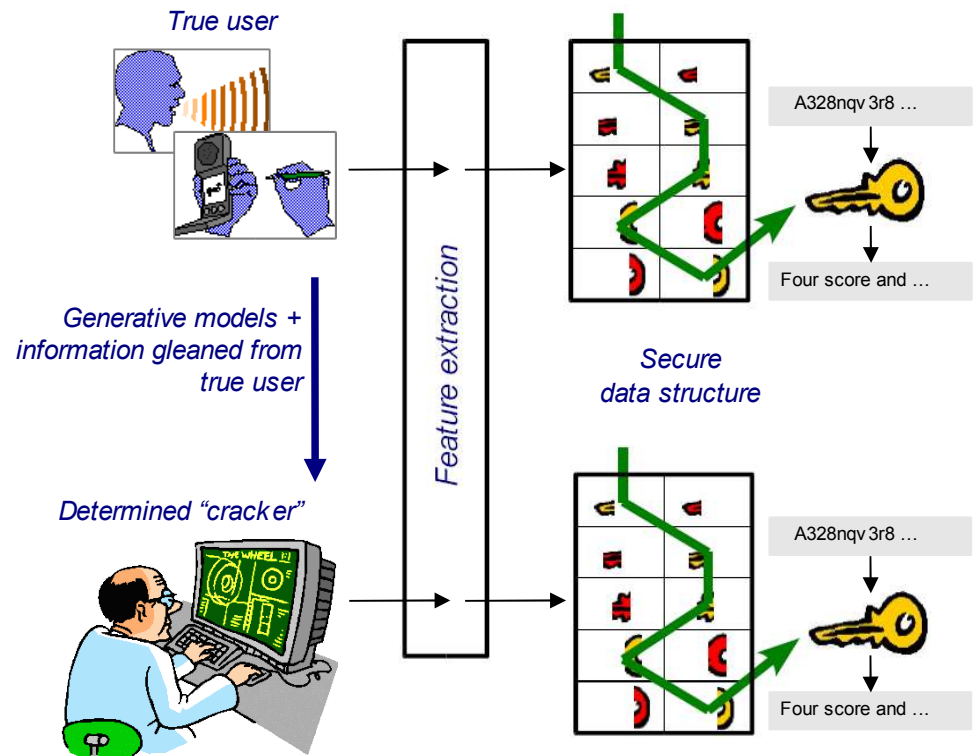
# Using Biometrics to Protect Data

Biometrics may be vulnerable:

- Generative models can mimic human behavior.
- If successful, some systems breakable.

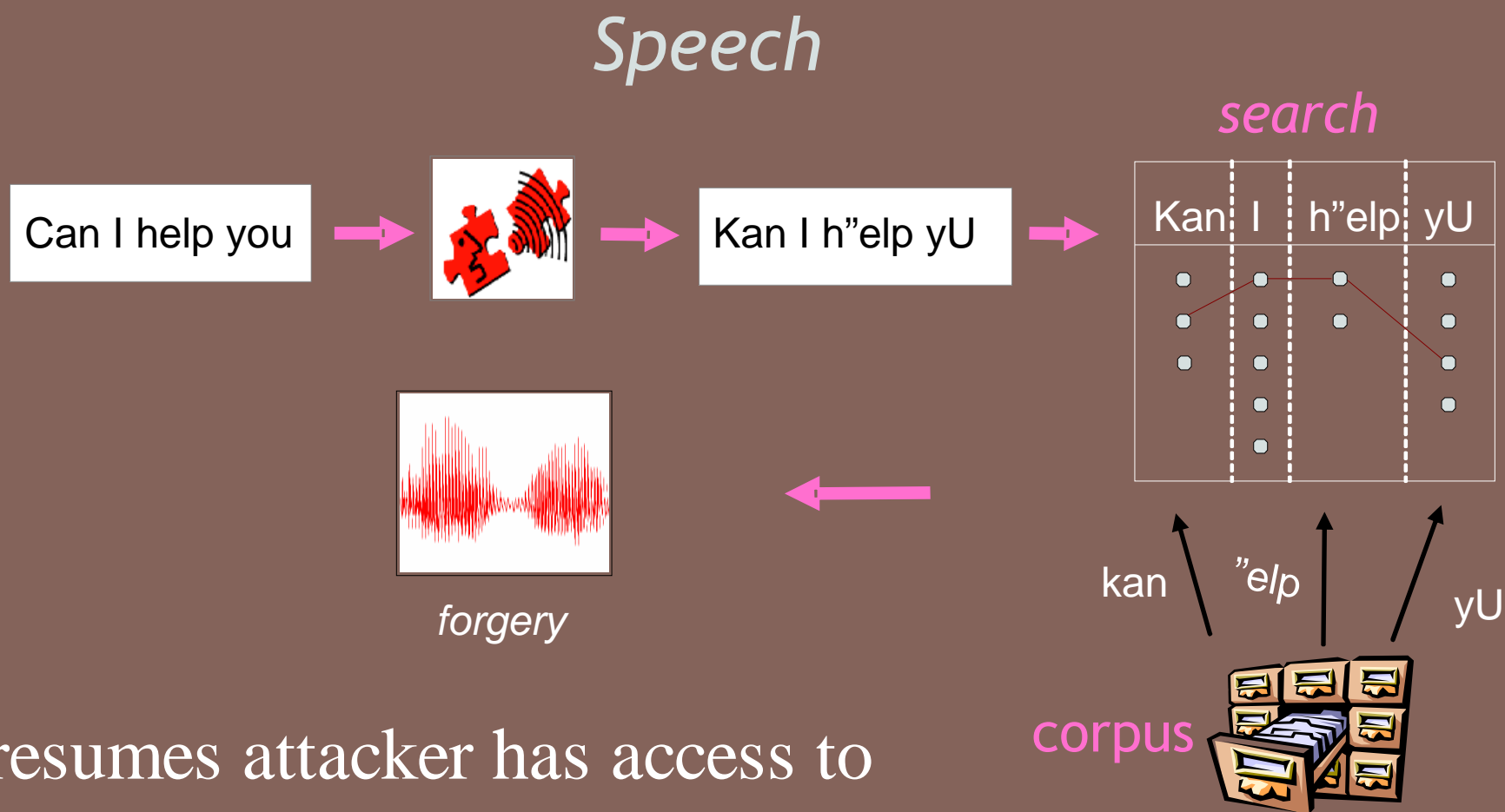
Our work:

- Identify potential attacks.
- Analyze risk.



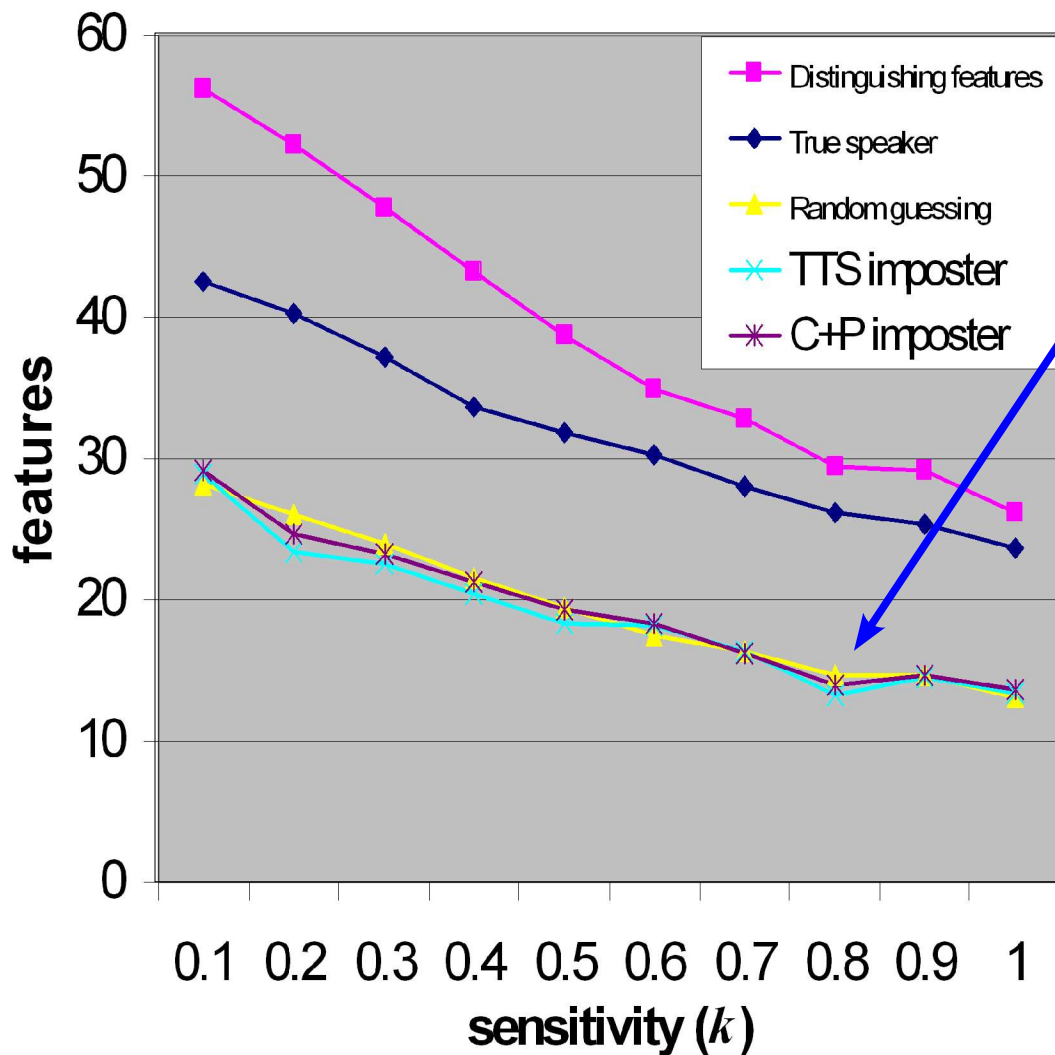
*Use our experience to improve biometric security.*

# Concatenative Attack on Speech



Presumes attacker has access to corpus of prerecorded speech.  
(Hack voice mail, record target with hidden mike, etc.)

# Results of Text-to-Speech Attacks\*



TTS is no better than random guessing. Why?

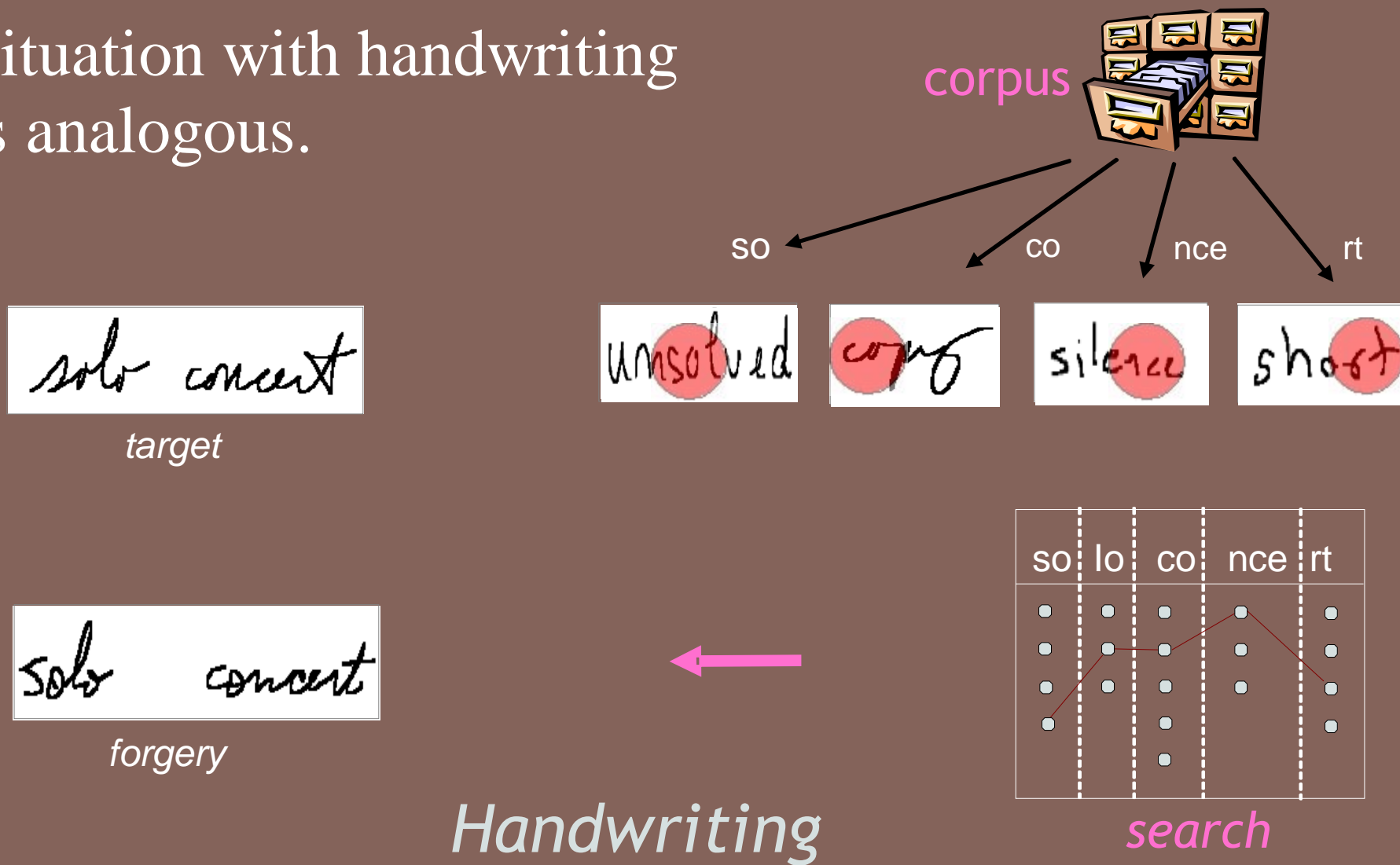
- Speech synthesis too immature at this point.
- We just didn't have enough data.

*Either way, we expect attacks to become more worrisome over time.*

\* "Towards Speech-Generated Cryptographic Keys on Resource-Constrained Devices," F. Monroe, M. Reiter, Q. Li, D. Lopresti, and C. Shih, *Proceedings of the Eleventh USENIX Security Symposium*, August 2002, San Francisco, CA, pp. 283-296.

# Concatenative Attack on Handwriting

Situation with handwriting is analogous.





# Investigations

In case of speech, we found concatenative attacks did no better than random guessing. Is same true for handwriting biometrics?

Models we studied

- Class 1* different user, different passphrase.
- Class 2* different user, true passphrase.
- Class 3* true user, different passphrase.
- Class 4* concatenation attack (true password constructed from unrelated writing).
- Class 5* true user, true passphrase (as baseline).

“The Effectiveness of Generative Attacks on an Online Handwriting Biometric,” Daniel Lopresti and Jarret Raim, *Proceedings of the Conference on Audio/Video Based Person Authentication*, July 2005.



# Biometric Hash from Handwriting

Studied published technique by Vielhauer, et al. for converting handwriting into secure 24-element hash.

Features extracted from each sample:

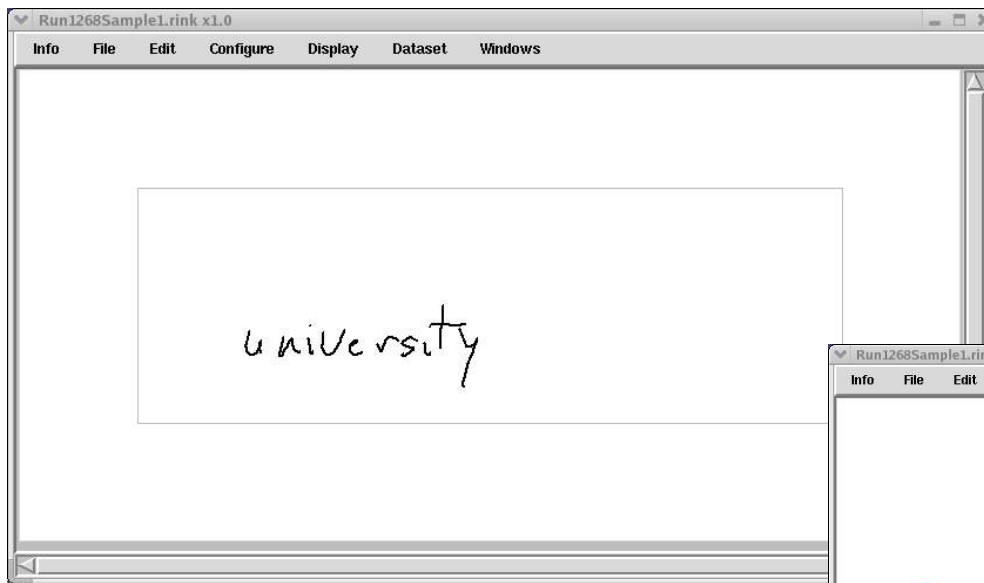
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1. Number of strokes
  2. Total writing time (ms)
  3. Total number of samples (points)
  4. Sum of all local (x,y) minima and maxima
  5. Aspect ratio (x/y) \* 100
  6. Pen-down / total writing time \* 100
  7. Integrated area covered by x signal
  8. Integrated area covered by y signal
  9. Average writing velocity in x
  10. Average writing velocity in y
  11. Average writing acceleration in x
  12. Average writing acceleration in y
  13. Effective writing velocity in x
  14. Effective writing velocity in y
  15. Integrated area under x, segment 1
  16. Integrated area under x, segment 2
  17. Integrated area under x, segment 3
  18. Integrated area under x, segment 4
  19. Integrated area under x, segment 5
  20. Integrated area under y, segment 1
  21. Integrated area under y, segment 2
  22. Integrated area under y, segment 3
  23. Integrated area under y, segment 4
  24. Integrated area under y, segment 5
- 

“Biometric Hash based on Statistical Features of Online Signatures,” Claus Vielhauer, Ralf Steinmetz, and Astrid Mayerhofer, *Proceedings of the Sixteenth International Conference on Pattern Recognition*, vol. 1, August 2002, pp. 123-126.

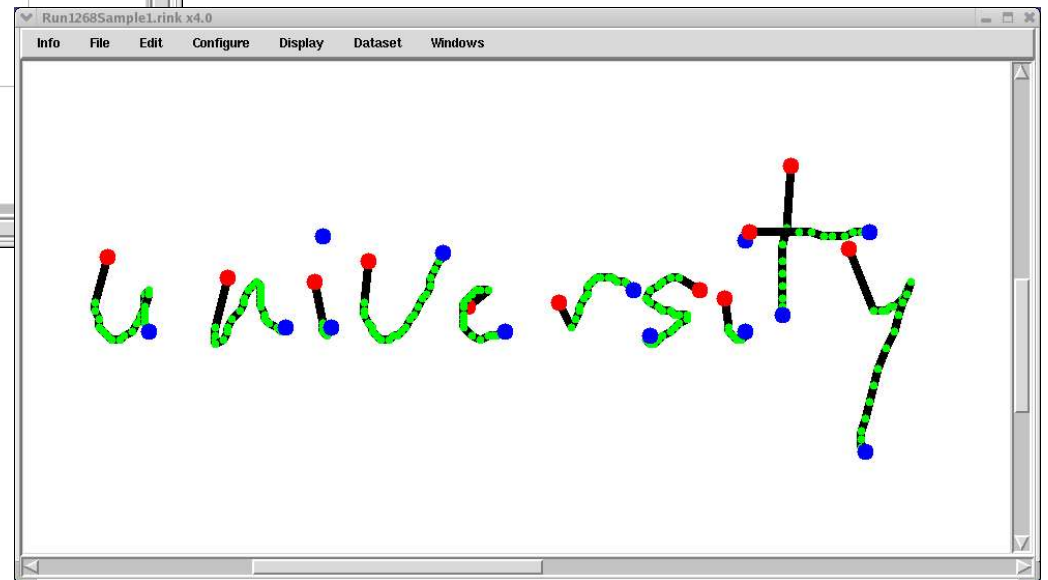
# Handwriting Features #1

Snapshots of our tool for ink capture written in Tcl/Tk:

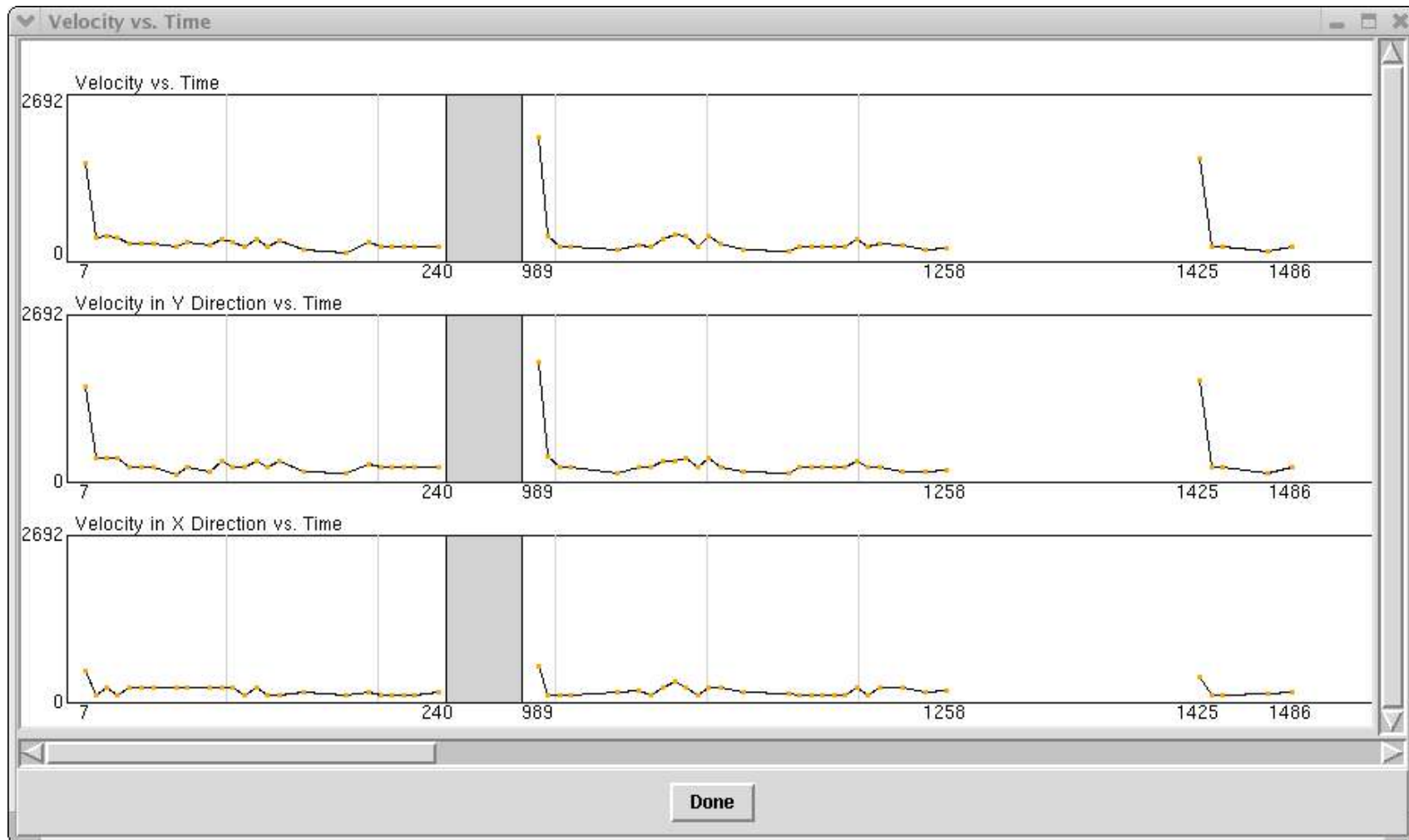


*Passphrase*

*Sampled points*

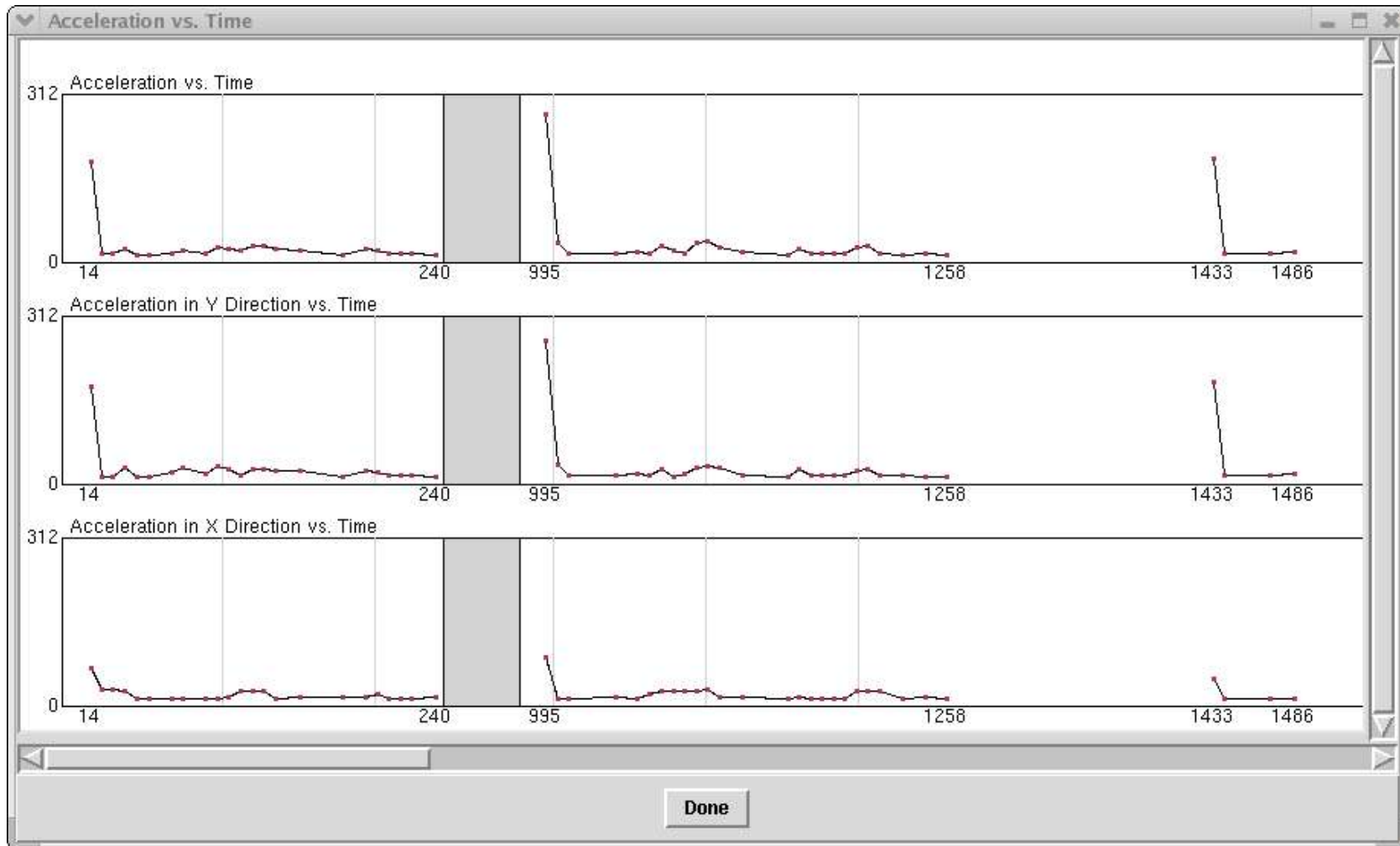


# Handwriting Features #2



*Snapshot of velocity profiles*

# Handwriting Features #3



*Snapshot of acceleration profiles*

# Typical Performance Evaluation

Traditional approach: conduct study using human subjects (naive and/or skilled “forgers”) and report False Reject Rate (FRR) and False Accept Rate (FAR).

- E.g., Vielhauer, et al. used 10 subjects who provided six samples and also tried to forge writing of other subjects based on static image.
- Average FRR was measured to be 7.0%.
- Average FAR was measured to be 0.0%.

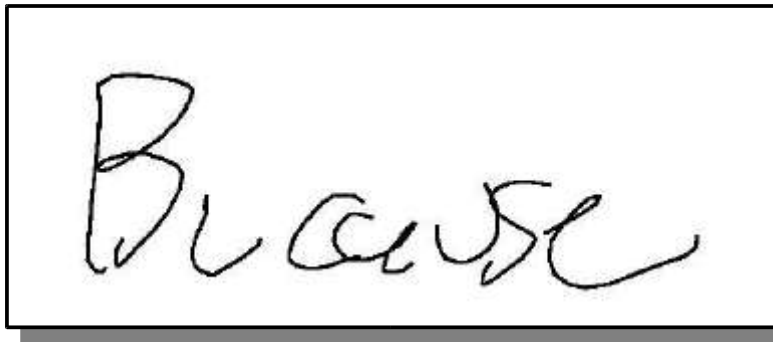
*This model misses the more ominous threat.*

“Biometric Hash based on Statistical Features of Online Signatures,” Claus Vielhauer, Ralf Steinmetz, and Astrid Mayerhofer, *Proceedings of the Sixteenth International Conference on Pattern Recognition*, vol. 1, August 2002, pp. 123-126.

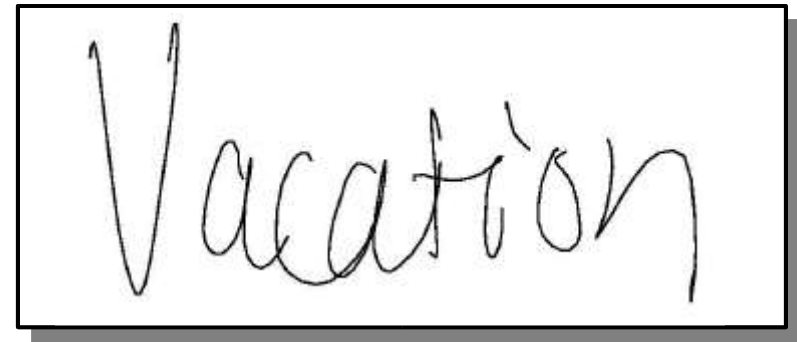
# Our Test Data

- Two writers each wrote four different passwords 20 or more times using Wacom Intuos tablet.
- Additional samples collected independently to support concatenative attacks.
- Dataset is small, but we are not trying to prove biometric is secure: we are studying its weaknesses.

Samples of handwriting we collected:



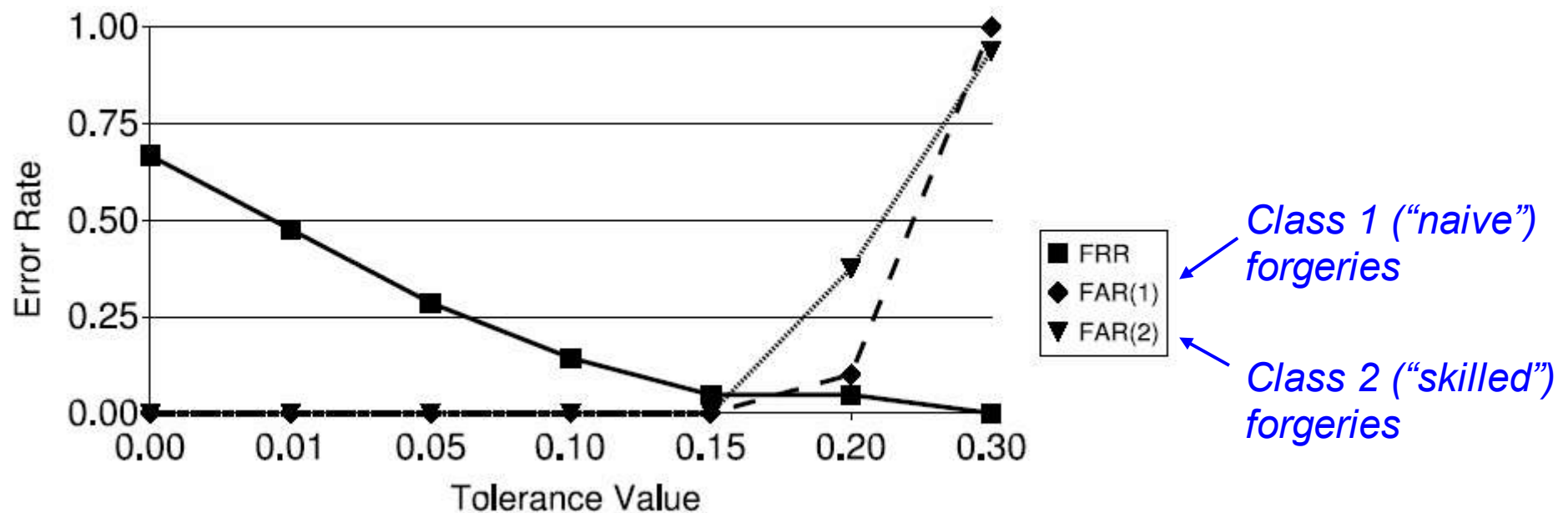
Brace



Vacation

# Determining Hash Tolerance

- Training set varied from 15 to 25 samples per class.
- Cross-validation performed using 5 to 10 samples.
- Various tolerances tested, most promising was 0.15.





# Concatenative Attack

- Separate corpus of writing samples collected and labeled on a per-character basis.
- Provides assortment of n-grams which can be selected to yield targeted password.
- Optimal concatenation can be formulated using dynamic programming, much like speech synthesis.

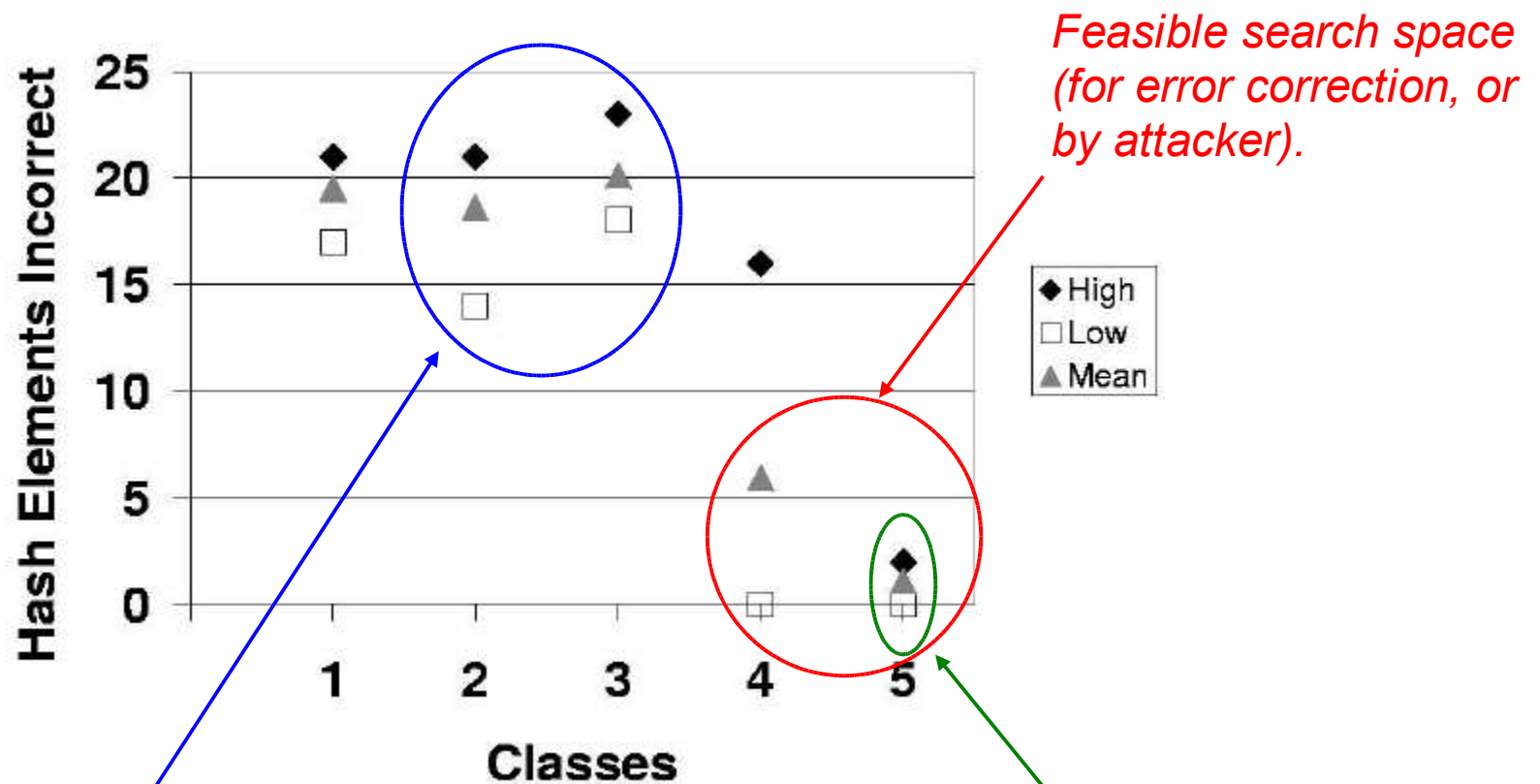
*Original passphrase*

*Parameters*

*Synthesized passphrase*

*parameters*

# Count of Incorrect Hash Elements

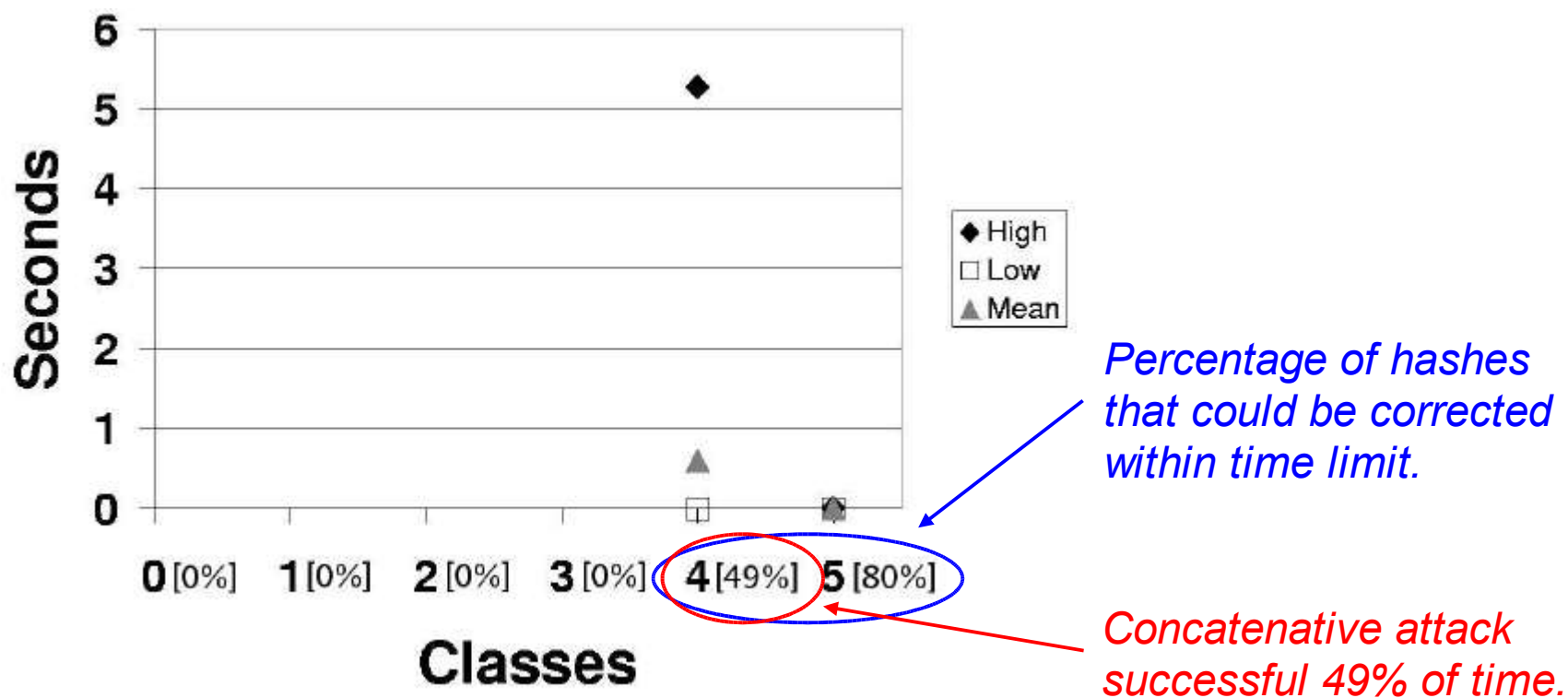


*Roughly same number of features sensitive to passphrase (Class 2) versus user (Class 3).*

*Even true user (Class 5) requires some post-error-correction.*

# Time to Correct Hashes

- Perform exhaustive search around hash vector.
- Timeout (failure) after 60 second time limit.
- Tests run on Pentium 4 PC, 3.2 Ghz, 1 GB RAM.



# Current Data Collection

In the midst of a new, larger-scale data collection:

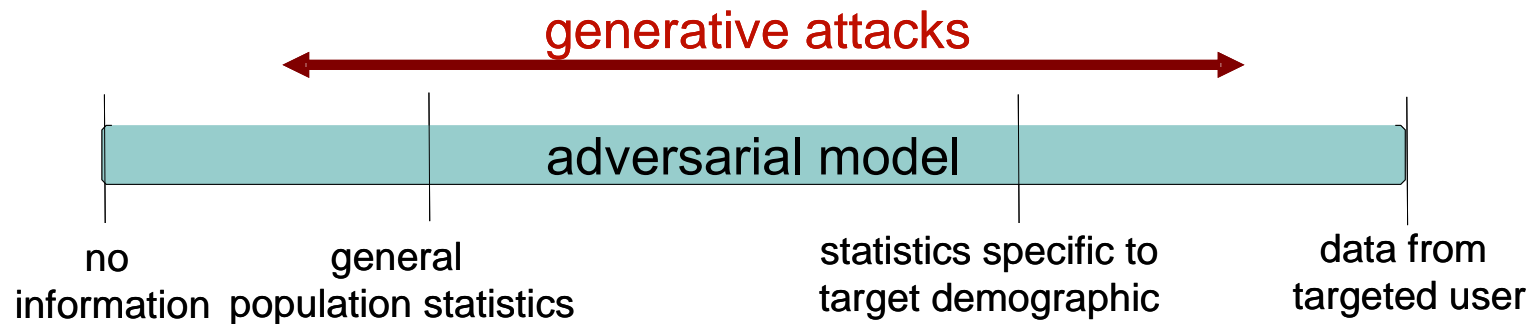
- Enlist ~100 users to write 5 passphrases 10× each on pen tablet computers (NEC, HP).
- Also have them write a general-purpose corpus to experiment with various generative attacks (guaranteed to cover all bigrams in passphrases).

Second phase (now beginning):

- Have users rewrite each passphrase 15 times.
- Ask users attempt to forge other user's writing after showing them static and/or dynamic view of target.

# Questions We Have

- Can an average user do a credible job as a forger?
- Are some users more susceptible to attack?
- Which generative models present the greatest risk (a number have appeared in the literature)?
- What kinds of knowledge give attacker advantage?



- Can anything be done to mitigate this risk (e.g., enforcing “good” passphrase choices)?

# Early Result

Dataset "userYYY", Sample #5

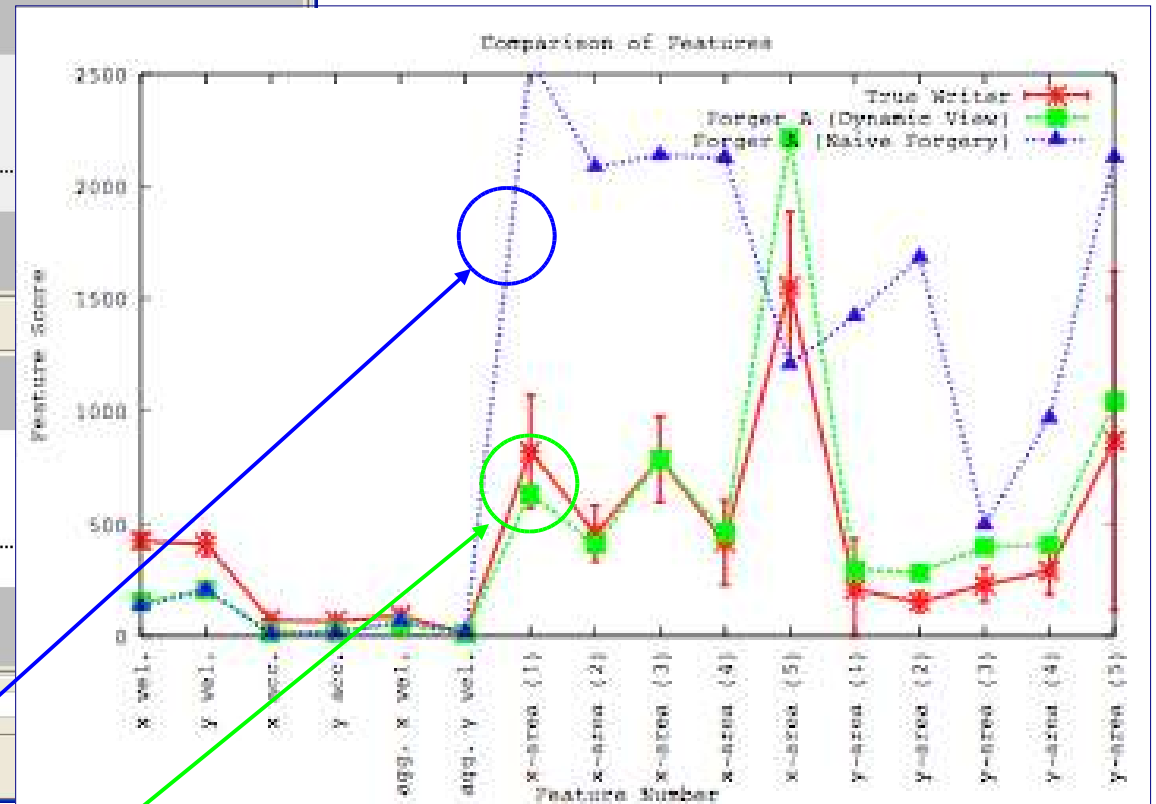
Please watch the handwriting below and then attempt to forge it:

**solo concert**

Redraw

Progress:

Pen Dot TCross Cross Clear Next



Naïve user

Forger with access to dynamic replay

online

offline

# Conclusions

- Generative models for human behavior present a threat to security of biometric systems.
- The traditional approach to performance evaluation, i.e., human studies involving “naive” and “skilled” forgers, is inadequate for assessing this threat.
- Full extent of this threat not yet characterized: much more work needs to be done.



# Acknowledgements

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