Carnegie Mellon

Hearing without Listening

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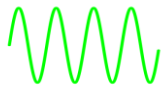
Recall

- Secure multi-party computation can be used to protect voice
- Enables the computation required for pattern matching without revealing the Alice's voice to the system Bob or Bob's system parameters to Alice
- Lets consider some real speech problems

A Brief Primer on Speech Processing Tasks



Biometrics

Speaker Verification

Speaker Identification

Speech Recognition

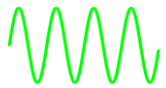
Are you really Bob? Yes/No (binary)

Which one of Alice, Bob, Carol, Dave, … **are you?** (multi-class)

You said ”hello, world!”

- All are pattern classification tasks

Privacy Challenges in Biometrics



Are you really Bob? Yes/No (binary)

Which one of Alice, Bob, Carol, Dave, … **are you?** (multi-class)

You said ”hello, world!”

Most common application: Verification

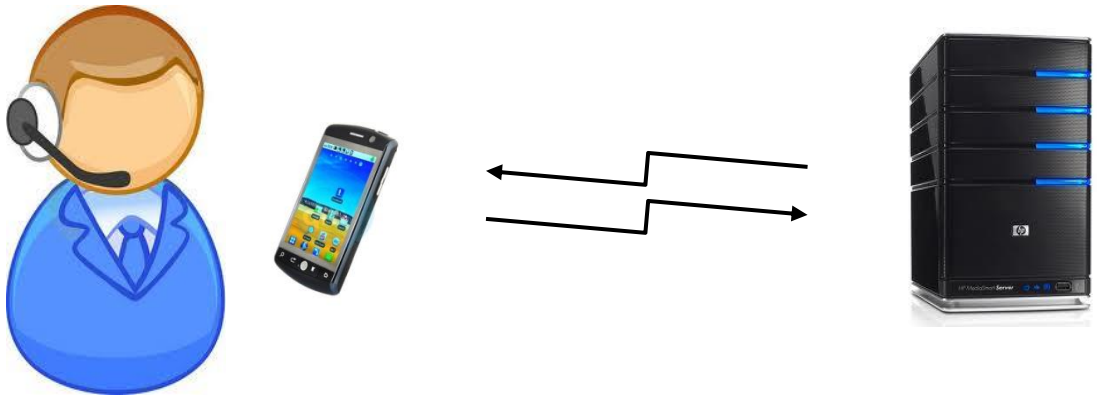
$$\hat{C} = \arg\max_{C \in \{\text{Target}, \text{Imposter}\}} Score(X; \Lambda_C)$$

- Task: Verify if a speaker is who he/she claims to be
- Setup: Speaker registers with the system in a registration phase
  - System builds model for speaker
- Operation: Speaker says something to the system
  - System compares recording to stored model

Verification: Privacy challenge

- Speaker does not trust system with his speech
  - System (or hacker) may abuse recordings
- Speaker does not trust system with model
  - System (or hacker) may abuse model
    - To detect speaker elsewhere
    - To impersonate speaker
- System must still verify the speaker accurately

Operational Setup

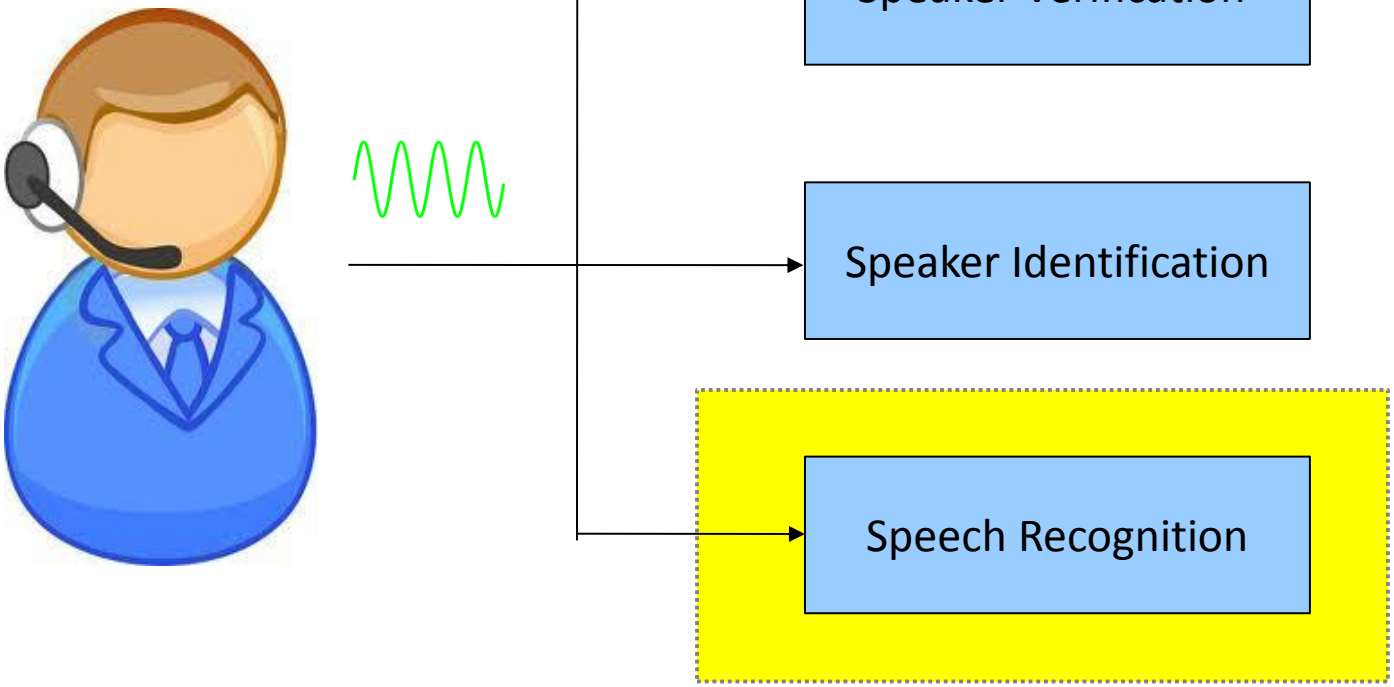


- User has a smart phone or computation capable device
  - Communicates with server using this device
- Encryption key maintained by device or user

Verification: SMC solution

- During registration system only sees *encrypted* version of user's speech
- System only retains an *encrypted* version of the model for the speaker
- System only receives encrypted version of speech during operation

Privacy Challenges in Recognition



Recognition Challenges

- Speech source distinct from recognizer
- E.g. User using remote recognition service
  - Recognizer must not see speech
  - Recognizer must not know result

- E.g. Data mining agency searching remote speech corpus for patterns
  - Recognizer must not see speech
  - Data corpus server must not see recognition result

Recognition: SMC Solution

- Speech remains encrypted
- Results are only available to the appropriate entity
  - User using remote service: Only user gets recognition output
  - Mining Surveillance: Mining agency only gets to know if target pattern was found

Privacy-Preserving Solutions

- SMC / Homomorphic encryption based solutions possible in all cases
  - Although details have not been worked out for *all* problems
- But how efficient are they?
  - Public key encryption is very expensive
  - Communication overhead is high
  - How expensive… ?

An Isolated Word Recognition Task

Activity	256-bit keys	512-bit keys	1024-bit keys
Alice encrypts speech	253 sec	1945 sec	11045 sec
Bob computes P(X|s) per HMM	80 sec	230 sec	461 sec
Bob compute P(X) per HMM	16 sec	107 sec	785 sec

- 10-word (digit) isolated word recognition task
  - HMM based recognizer
- 3.2GHz Pentium 4
- Time taken for computing the scores of all models *per second* of speech
  - Does not include communication overhead
  - Paillier cryptosystem
- Greater security with larger keys..

- Recognition accuracy identical to that obtained without privacy worries
  - Regular computation

A Speaker Verification Task

- Using primitives-based SMC

Steps	Time (256-bit)	Time (1024-bit)
Encrypting $\bar{x}_t$ $\forall t$	138 s	8511 s
Evaluating Adapted	97 s	1809 s
Evaluating UBM	same as adapted	same as adapted
Comparison	0.07 s	4.01 s
Total $=E[\bar{x}_t]$ + adapted + UBM + compare	331 s $\sim$ 5.47 min	12133 s $\sim$ 3 hr, 32 min

- Computation details per second of incoming speech
  - Core-2 duo, 2 GHz
  - BGN cyrptosystem (Paillier an order of magnitude faster)
  - Does not include communication overhead
- "Insecure" computation: Negligible time
- Classification accuracies indistinguishable from insecure version

Other Possible Contributions to Cost

- Have not considered many conventional processing steps
  - Speech Rec: *Pruning* reveals information
    - Not pruning makes recognition computationally infeasible for most tasks
  - Verification: Factor analysis methods add complexity
- Protecting against malicious users, e.g. through zero-knowledge proofs, is *much* more expensive
- Training on private data (e.g. for verification) is particularly expensive

Efficiency

- More efficient implementations and protocols possible
  - 10 to 100x faster
  - Techniques based on garbled circuits can be very fast
  - *STILL TOO SLOW*
- Better homomorphic cryptoschemes?
  - Don’t expect dramatic improvements anytime soon

The 1-mile view

- Privacy-preserving pattern matching tasks are possible
  - Work required on improving security under malicious model
- Have seen a “Cryptographic” approach
  - Based on Encryption
  - “Correctness” based – result with “secure” computation must be identical to that with regular computation
- But computationally infeasible
- Do we have an alternate approach?..

An Alternate Perspective

Encryption-based Mechanisms

- Encryption-based techniques attempt to retain *all* information
  - Final computation must be identical to what we would obtain without encryption
- Encryption-based techniques assume *everything* about the speech must be hidden
  - No inference must be possible at all outside of pattern matching results

Alternate Setup: *Usable* Privacy

- Do not need perfect Encryption
  - Just enough to discourage
- Do not need identical results to non-private computation
  - Similar results will suffice..
- In following slides, use speaker verification as platform

Password based schemes

- Text passwords are safe and efficient
  - Highly secure
  - Near instantaneous response
- Reason: *Based on exact match*
  - System stores text password encrypted by a one-way hash function
    - E.g. SHA-*
    - Even the *system* cannot decrypt
  - Incoming passwords are encrypted identically
  - Encrypted incoming password is matched to stored encrypted password

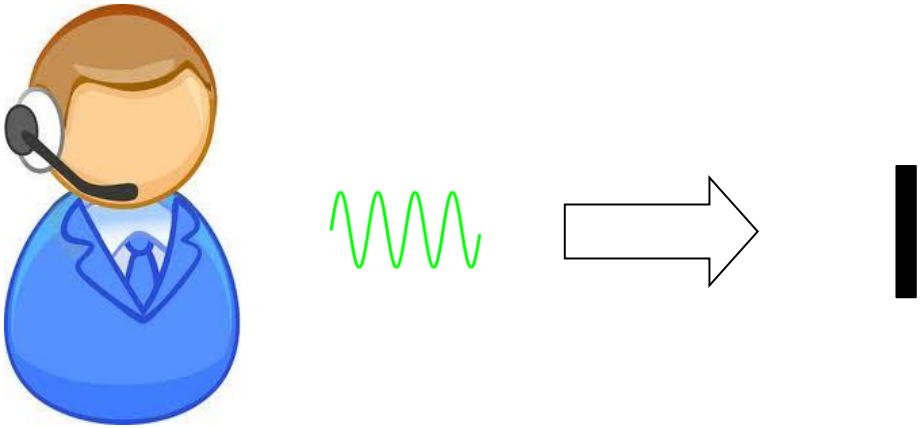
- **Cryptographic hash functions are extremely fast to compute**
  - Can we use a similar process?

Speaker Verification as String Matching

Simple approach:

Convert speech into a “password”

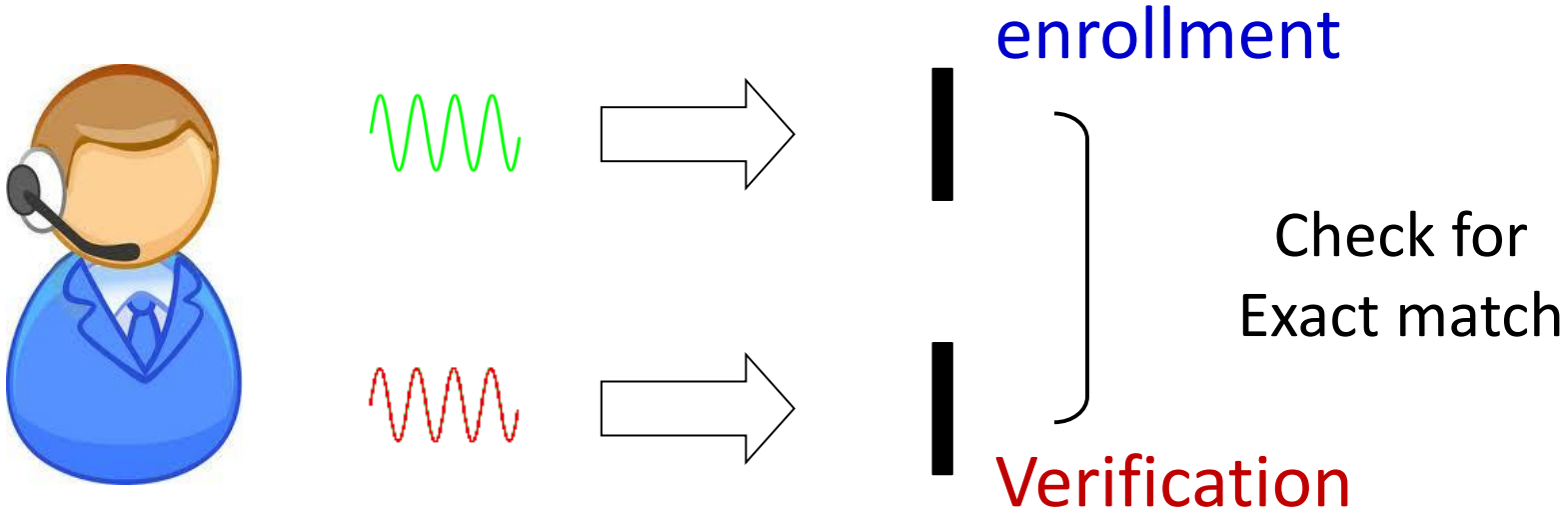
- ***Uninformative*** fixed-length bit string



Similar to password systems

Speaker Verification as String Matching

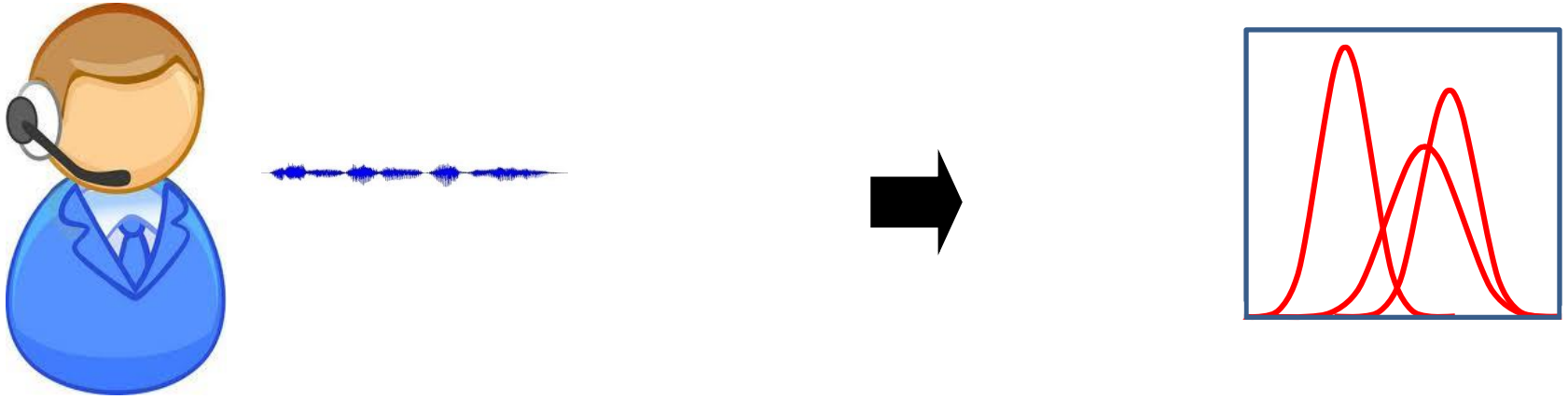
Speaker Verification by comparing bit strings



- **Problems**:
  - How do we convert speech to fixed length bit string?
    - Speech recordings vary in length
  - How to work with exact match?
    - Enrollment and test recordings never identical

Converting Speech to Fixed-Length Representations: Supervectors

- Typical approach: Estimate the distribution of the measurements in the recording



Concatenate the distribution parameters

supervector $s = (\mu_1 \,||\, \ldots \,||\, \mu_M)$

Supervectors

- The Supervector for any recording represents the distribution of feature vectors in the recording
- The length of the supervector is fixed, regardless of the length of the recording
- I.e. a fixed-length representation of the recording

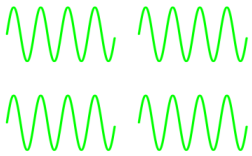
Verification: Modified Approach

- System obtains multiple enrollment recordings $\mathbf{X}_1$, $\mathbf{X}_2$, … from the speaker
- System generates supervectors S_1, S_2.. for each enrollment recording

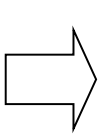
- System obtains a collection of *imposter* recordings
- System generates supervectors I_1, I_2, ... for each imposter recording

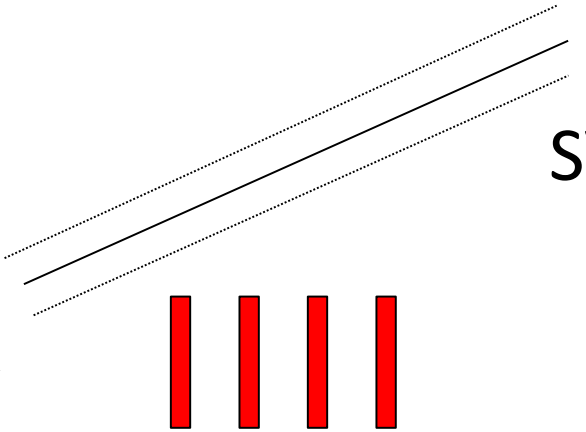
Verification by Supervectors

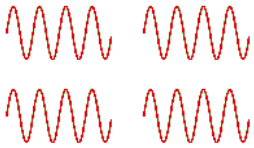
Train SVM classifier across the speaker & imposter supervectors



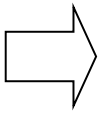
speaker







imposter



For a “Password” Version

- Supervectors are good fixed-length representations of the audio
  - But are informative
- Can they be converted somehow to uninformative “password” strings?
  - On which we can expect *exact match* for authentication?
- Recall
  - **Text-based password systems use cryptographic hashes..**

Locality Sensitive Hashing

- Locality sensitive hashing [Indyk & Motwani, 1998] is a method of mapping data to bit strings or *keys*:

  $X \rightarrow H(X)$

- It has the following property:
  - The hash keys H(X) and H(Y) of X and Y are identical with high probability if d(X,Y) is small (for some distance function d())
  - H(X) and H(Y) are different with high probability if d(X,Y) is large
- The function H(X) depends on the definition of d(X,Y)

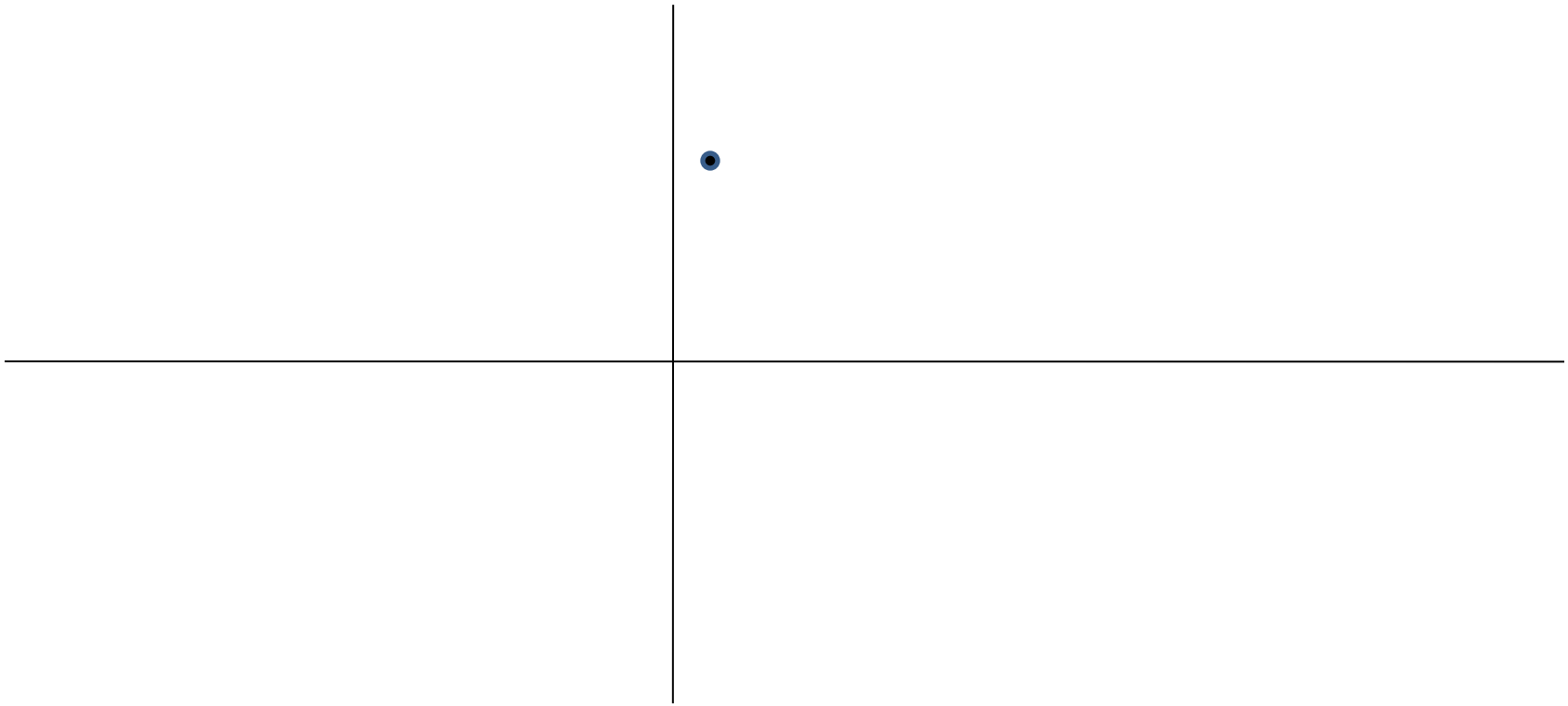
LSH with Euclidean Distance

- A vector X gets converted to a vector of M numbers $\mathrm{H(X)} = [\mathrm{h_1(X)}\ \mathrm{h_2(X)}\ \mathrm{h_3(X)}\ \ldots\ \mathrm{h_M(X)}]$

$$h_i(X) = h_i(X; V_i, b_i) = \left\lfloor \frac{X^T V_i + b_i}{w} \right\rfloor$$

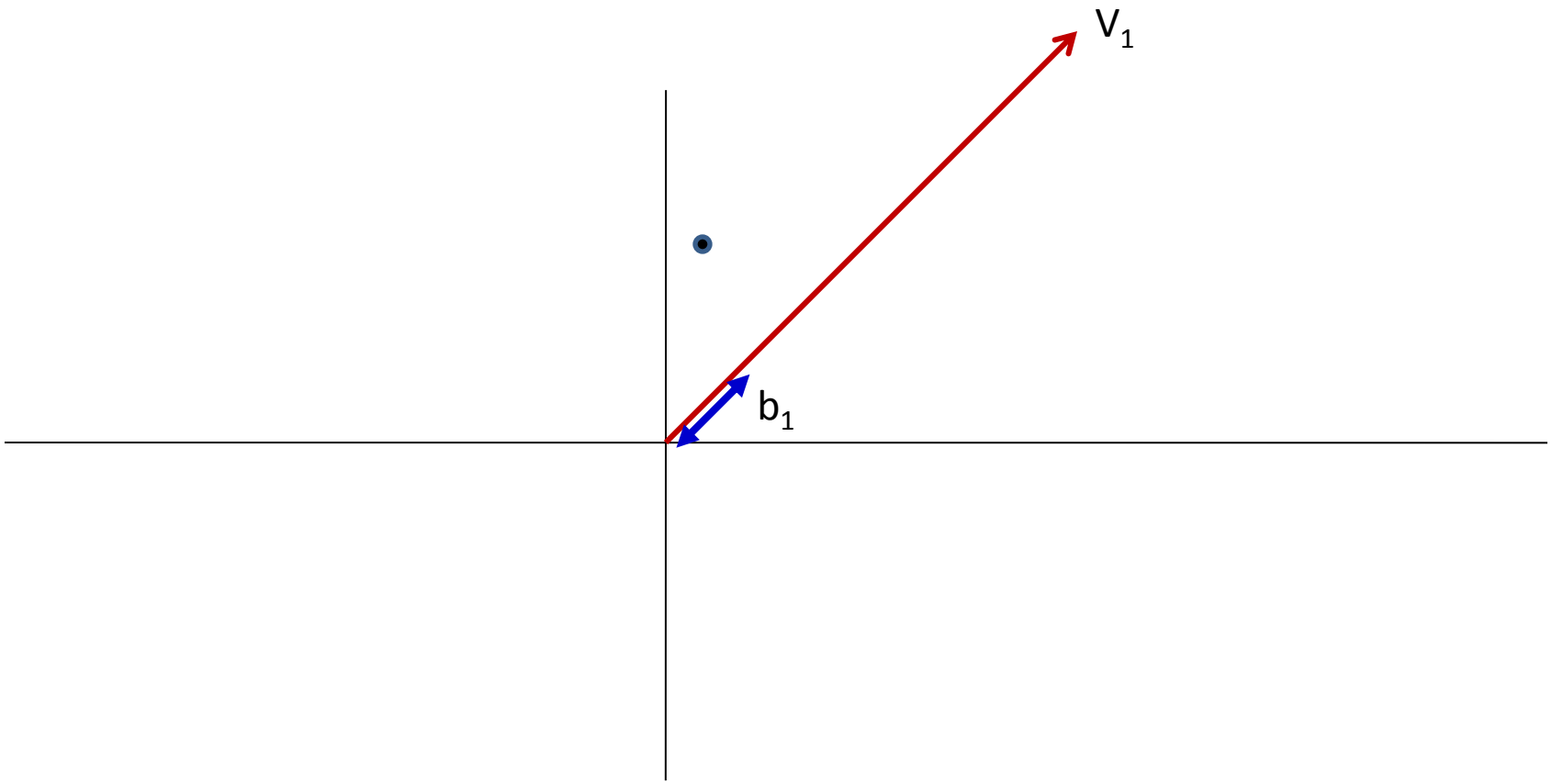
- V_i is a random vector drawn from a normal distribution
- b_i is a random number between 0 and w
- w is the quantization width

Euclidean LSH



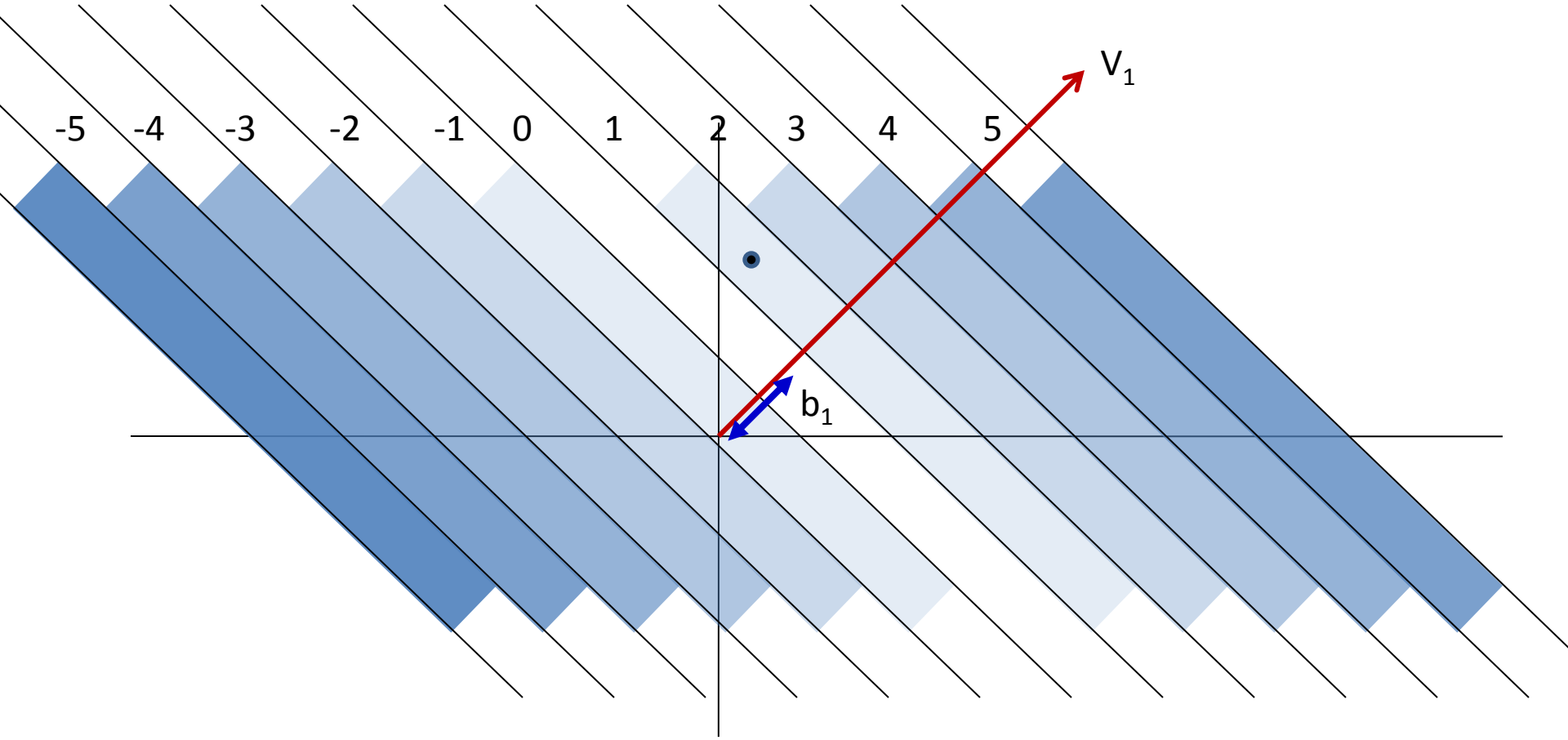
- A 2-D example

Euclidean LSH



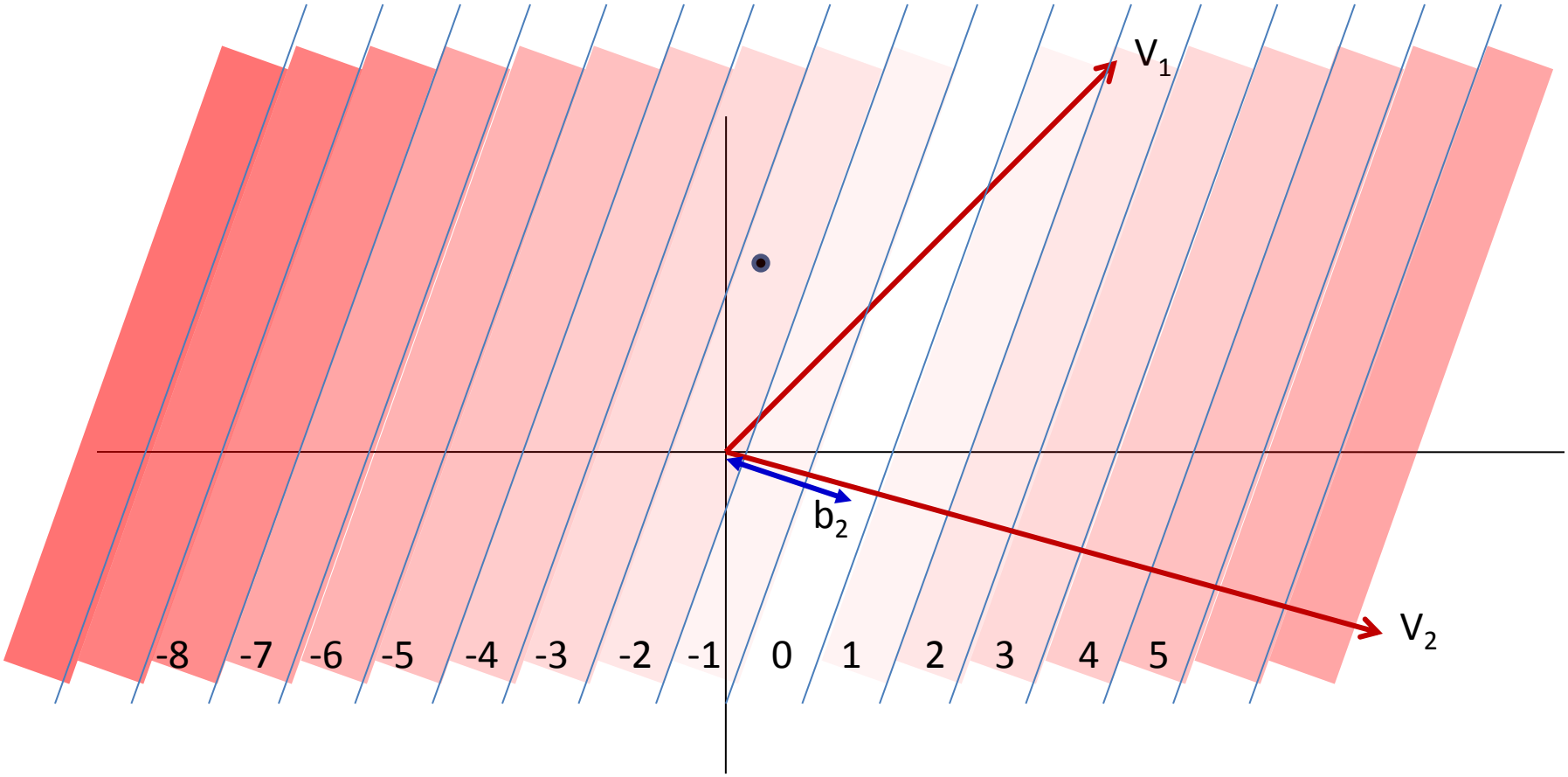
- A 2-D example
- The first component in the hash key: $h_1(X)$

Euclidean LSH



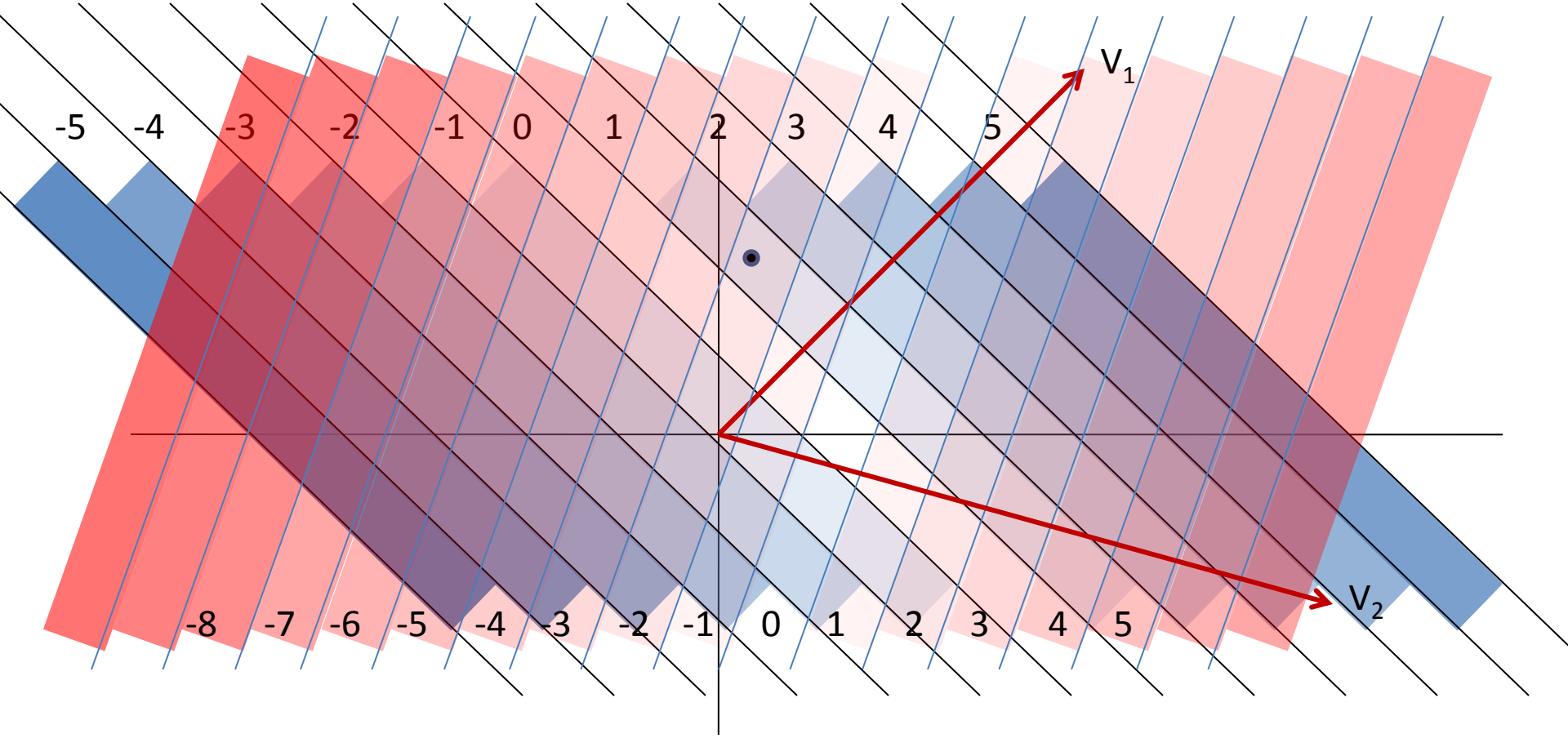
- A 2-D example
- The first component in the hash key : $h_1(X) = 1$

Euclidean LSH



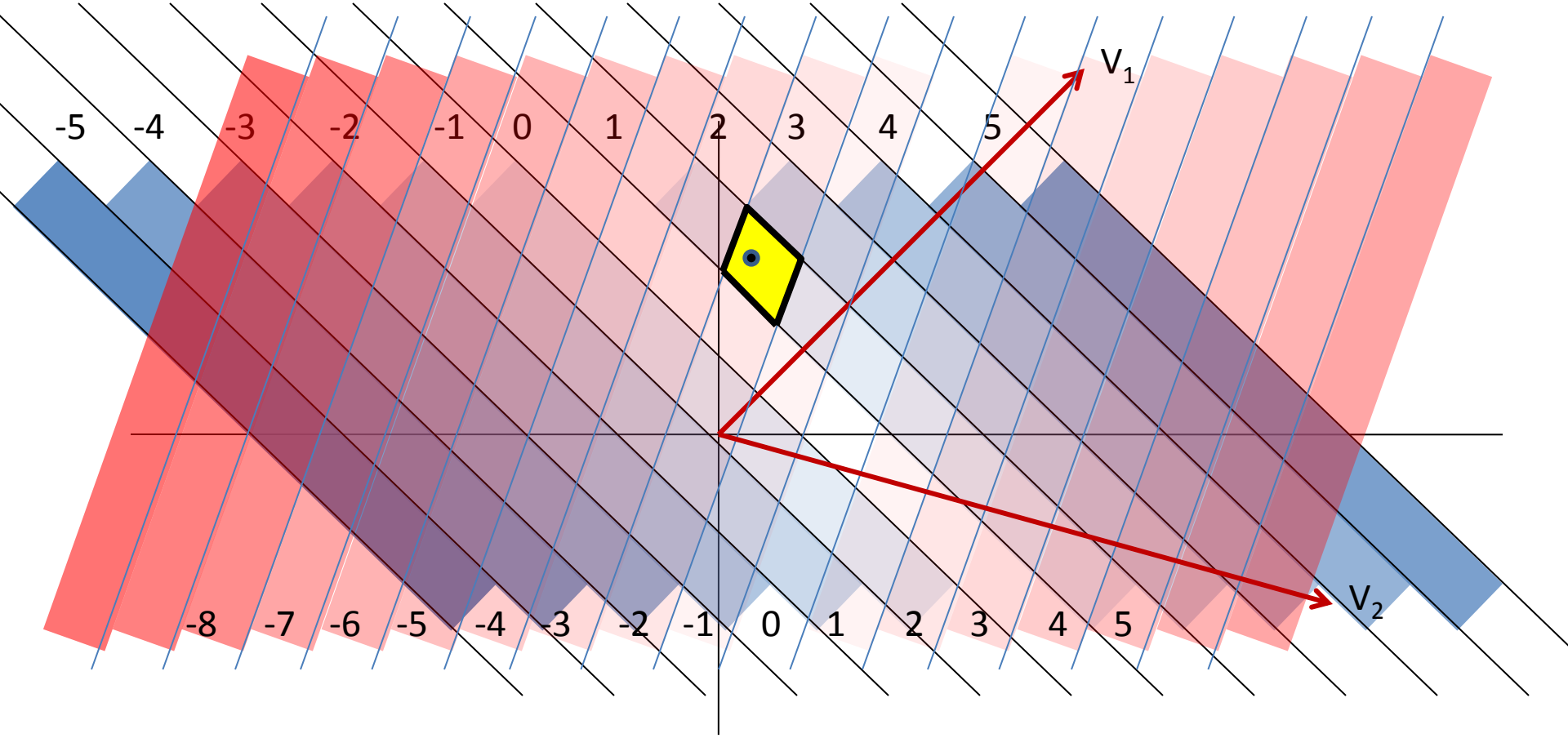
- A 2-D example
- The second component in the hash key : $h_2(X) = -2$

Euclidean LSH



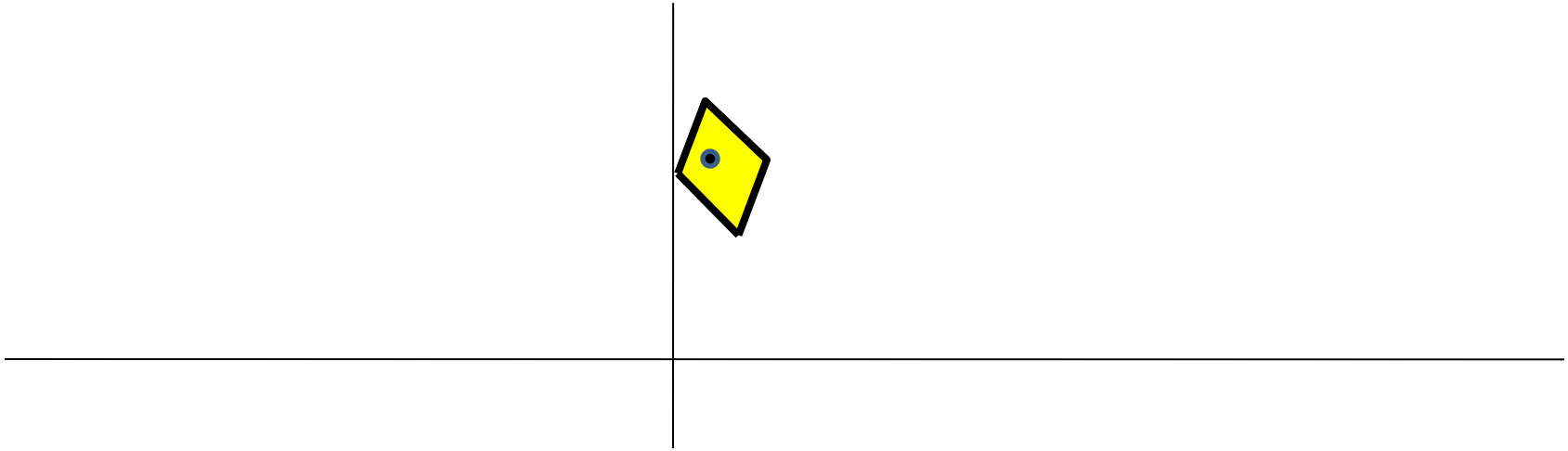
- $H(X) = [h_1(X)\ h_2(X)] = [1\ -2]$

Euclidean LSH



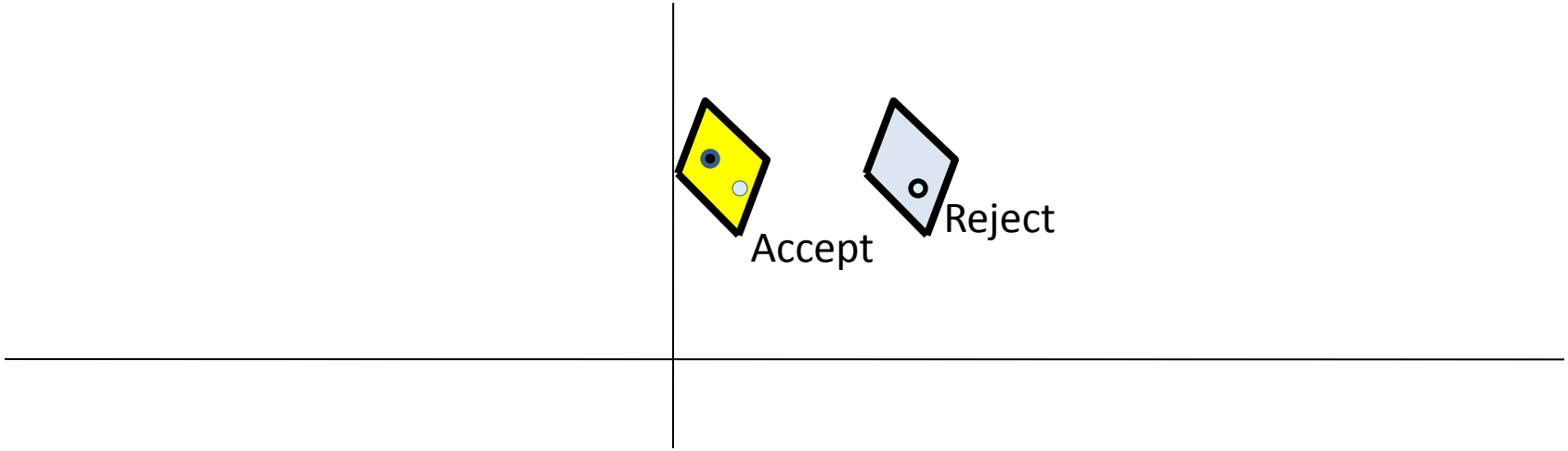
- H(X) = [1 -2]
- All vectors in the highlighted cell will have the same LSH key

Speaker Verification with Euclidean LSH



- Enrollment: Assume one enrollment utterance
  - Convert the supervector for the enrollment utterance to a hash key
    - Find a random cell in which it resides

Speaker Verification with Euclidean LSH



- Test: Find the hash key for the test supervector
  - Find the cell it resides in
- If its identical to the enrollment key, accept
  - Test and enrollment utterances are in the same cell
- Else reject
  - They are in different cells

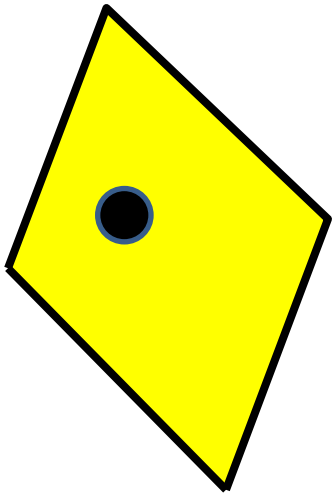
Securing the Key

- LSH keys are informative
- BUT : Two vectors in the same cell have exactly the same key
  - Even if the key is cryptographically hashed!
- **Apply a cryptographic hash to the LSH key**
  - ***User* retains the private key to cryptographic hash**
- **Converted speech to *uninformative* bit strings**
  - **On which comparison can be performed via exact match!**
- In all subsequent discussion, we assume that LSH keys are cryptographically hashed!
  - And are uninformative

The size of the cell

- Increasing the number of components in **H**(X) makes the cell smaller
- **H**(X) = [h_1(X) h_2(X)]

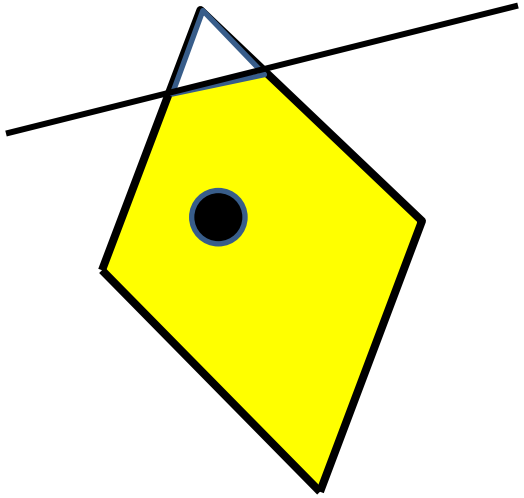
  = [1 -2]



The size of the cell

- Increasing the number of components in **H**(X) makes the cell smaller
- **H**(X) = [h_1(X) h_2(X) **h_3(X)**]

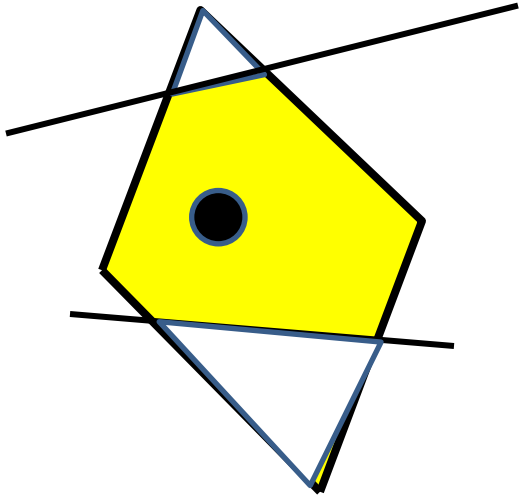
  = [1 -2 **7**]



The size of the cell

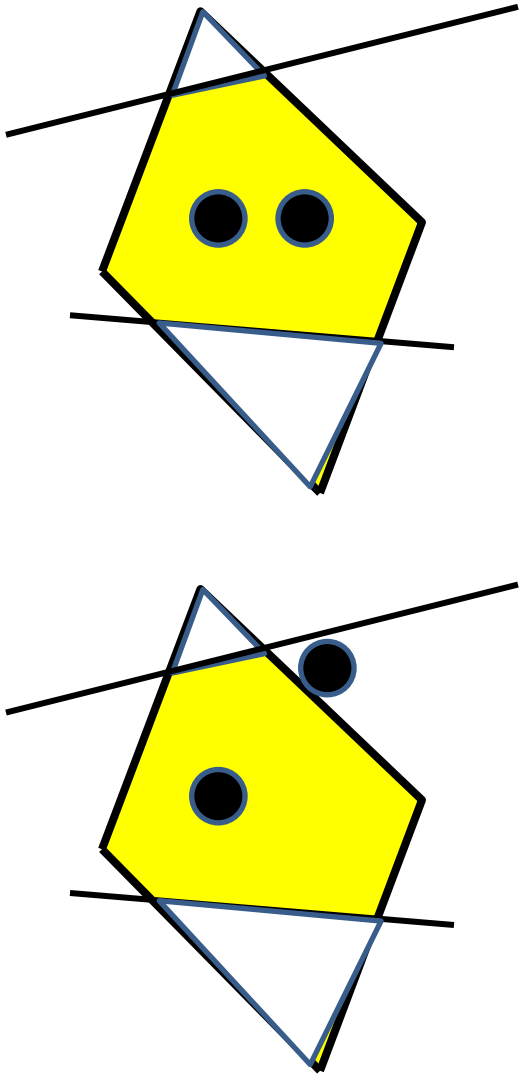
- Increasing the number of components in **H**(X) makes the cell smaller
- **H**(X) = [h_1(X) h_2(X) **h_3(X) h_4(X)**]

  = [1 -2 **7 0**]



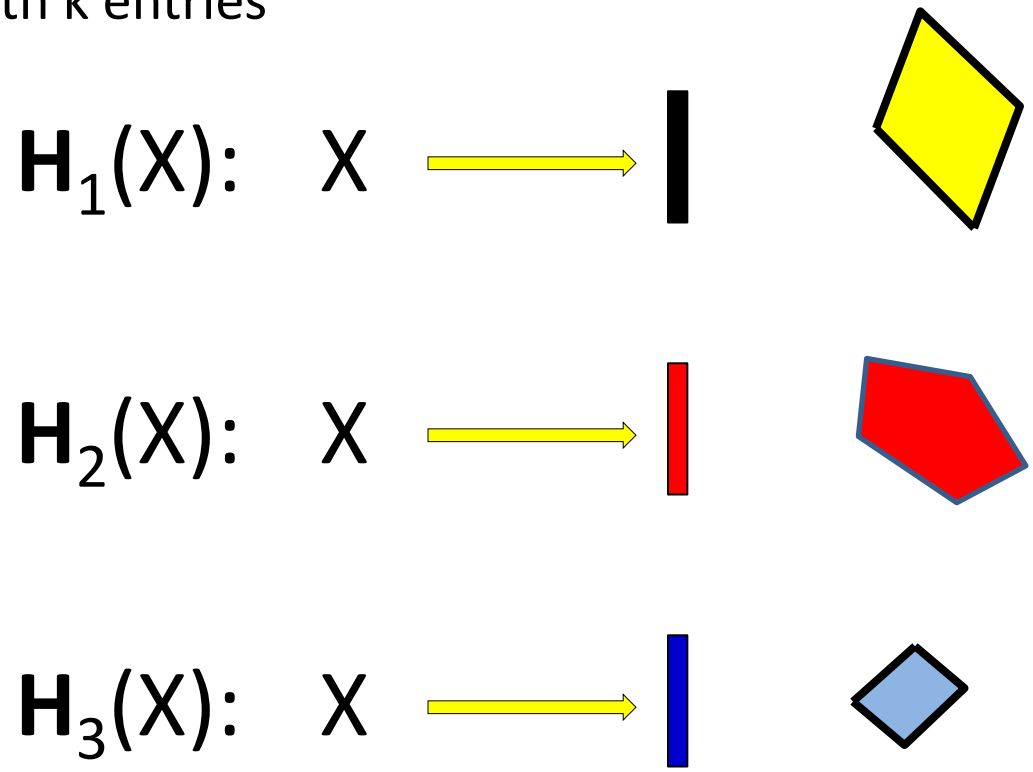
The size of the cell

- Increasing key length → reduced cell size
- Reduced cell size → more likely that two vectors that fall in the same cell (have same LSH key) belong to the same speaker
  - Very Good!
- Also makes it *more* likely to *miss* valid vectors
  - Which may fall outside the cell simply because of the vagaries of its shape



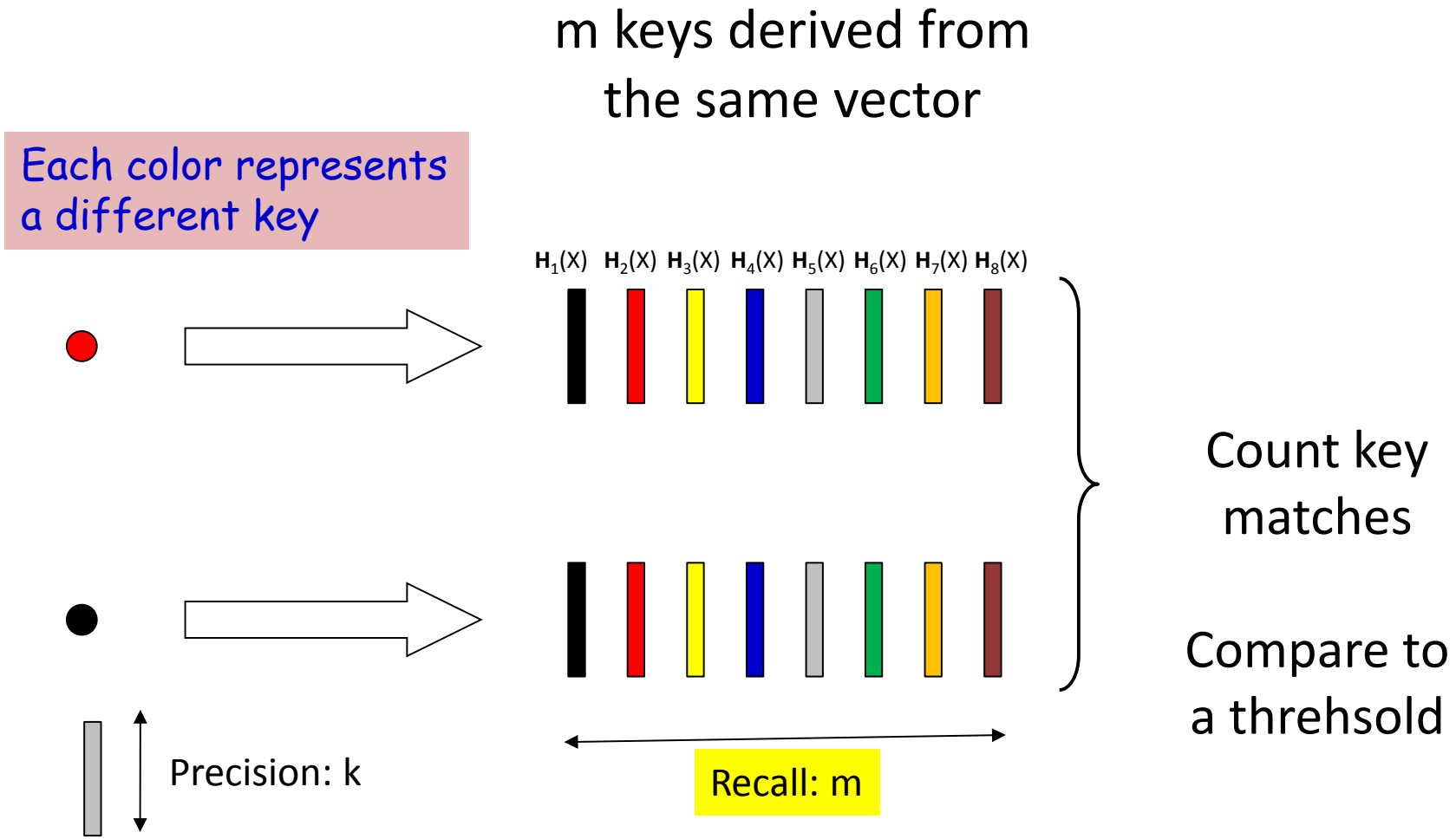
Solution: Use many LSH keys

- Use multiple LSH Hash functions to produce multiple LSH keys
  - Each with k entries



- Each key represents a cell of a different shape and size

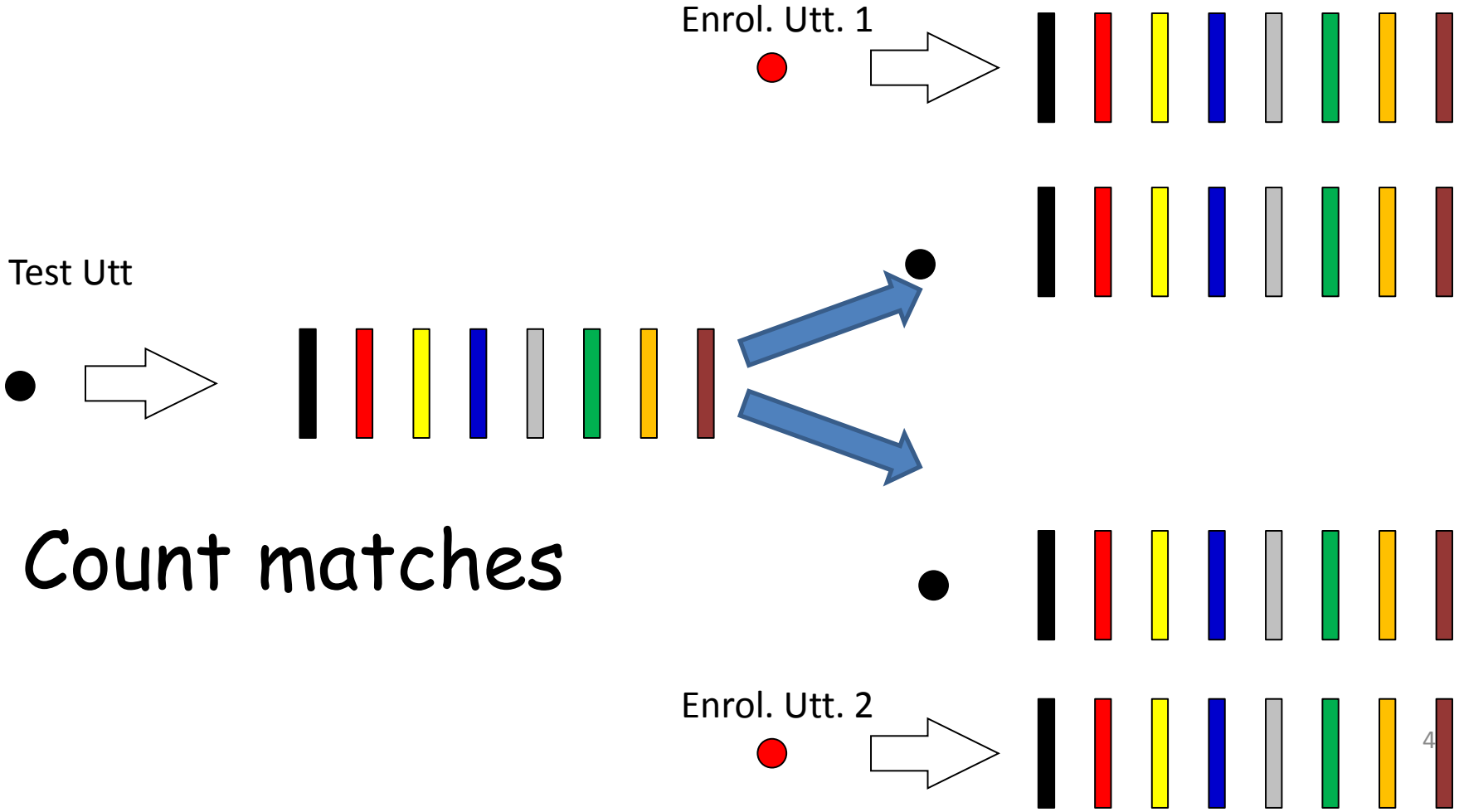
Using multiple LSH functions



Multiple Enrollment Utterances

- A single enrollment utterance is insufficient
- Usually multiple enrollment utterances

Cartoon of Authentication Process



Overall LSH-based Procedure

- **The User obtains a set of (vector) Hash functions**

  $\mathbf{H}_1(.), \mathbf{H}_2(.), \ldots$

  – From the system

- **Enrollment:**
  - User records a set of enrollment utterances $X_1, X_2, ..$
    - And computes supervectors from all of them
  - User computes keys $\mathbf{H}_1(X_1)\ \mathbf{H}_1(X_2)\ ..\ \mathbf{H}_2(X_1)\ \mathbf{H}_2(X_2)\ldots$
    - **Encrypts them with SHA (and retains SHA key)**
    - And sends them to the system
  - **The system stores all encrypted hashes**

Overall LSH-based Procedure

- **Verification**:
  - User records test utterance Y
  - User computes $\mathbf{H}_1(Y)$ $\mathbf{H}_2(Y)$ …
  - User sends keys to system
  - System counts
    - Score = $\Sigma_i \Sigma_J$ $H^j(Y) == H^j(X_i)$
  - If Score > threshold : Accept
  - Else reject

Experiments

LSH & cryptographic hash functions are fast

- For 200 LSH keys per instance overhead was 28 ms!
- Negligible compared to the protocol using homomorphic encryption
  - Independent of the sample length

Experiments

Error on YOHO dataset (EER)

LSH	13.80%	SVM	9.1%

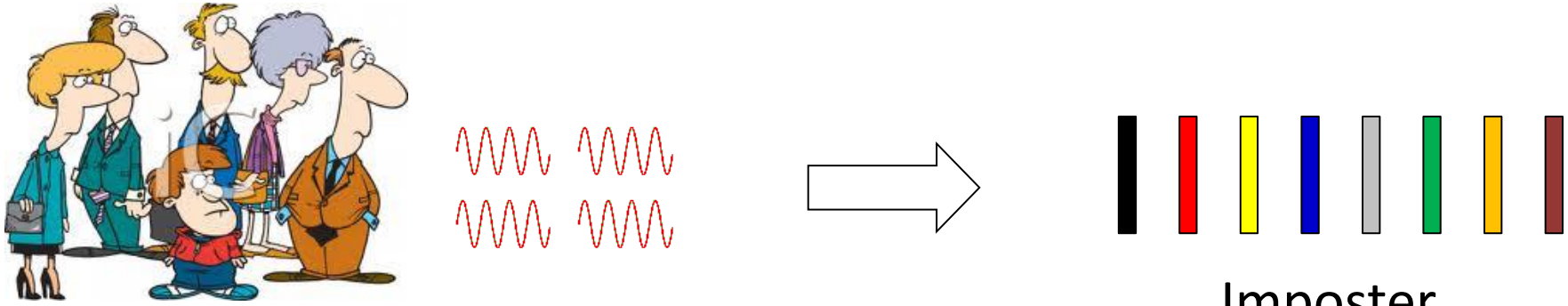
Negative Instance

- Solution so far only considered *positive* instances of data
  - I.e. only consider closeness to enrollment instances from speaker

- Ignore the nature of *imposter* data

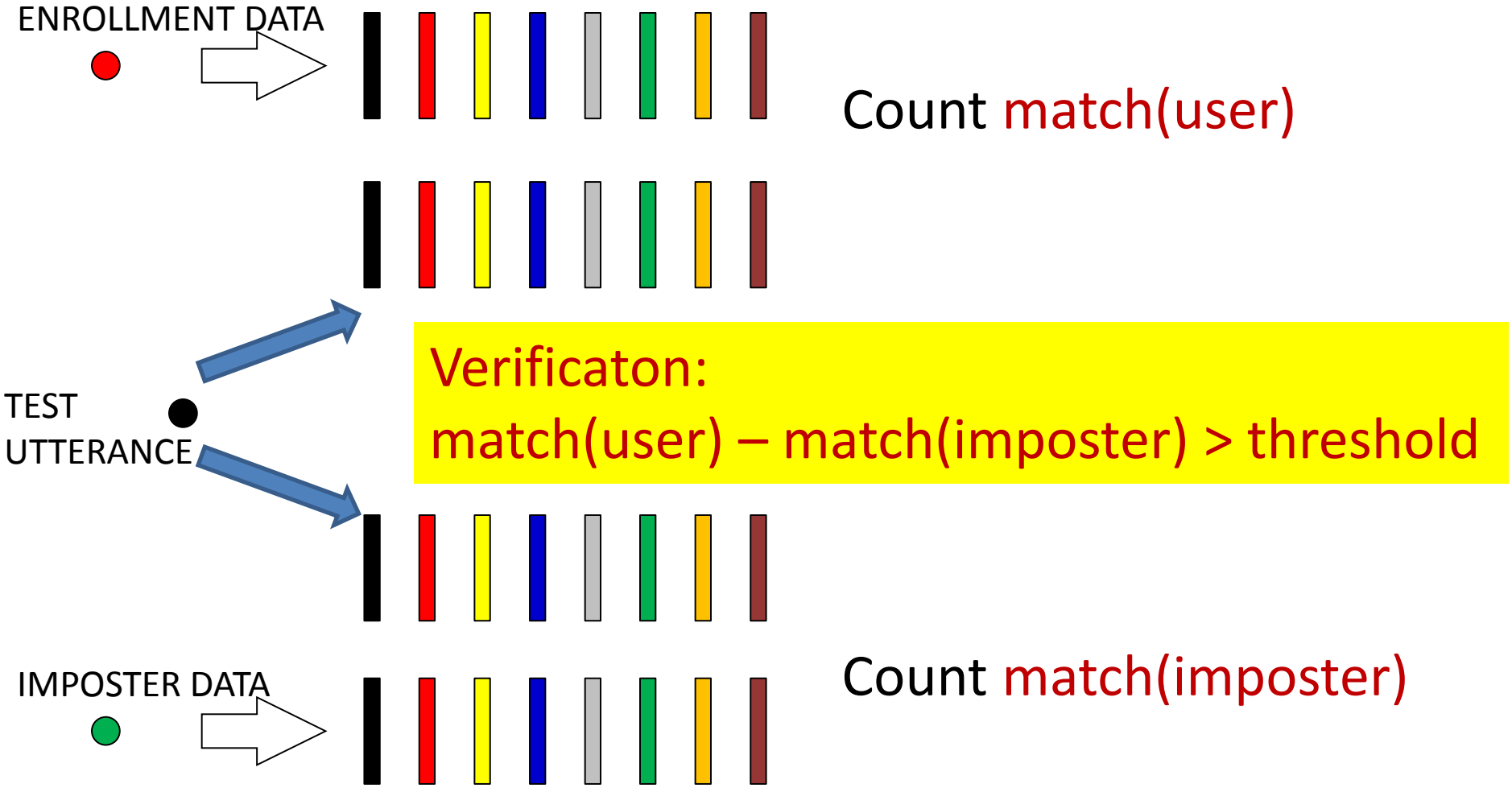
Imposter Data

Improvement : Also use LSH keys from imposter data



- User may records or *generate* imposter data
  - **Record**: download from trusted repository, or from server
  - **Generate**: Algorithms exist for generating negative instances

Considering imposters

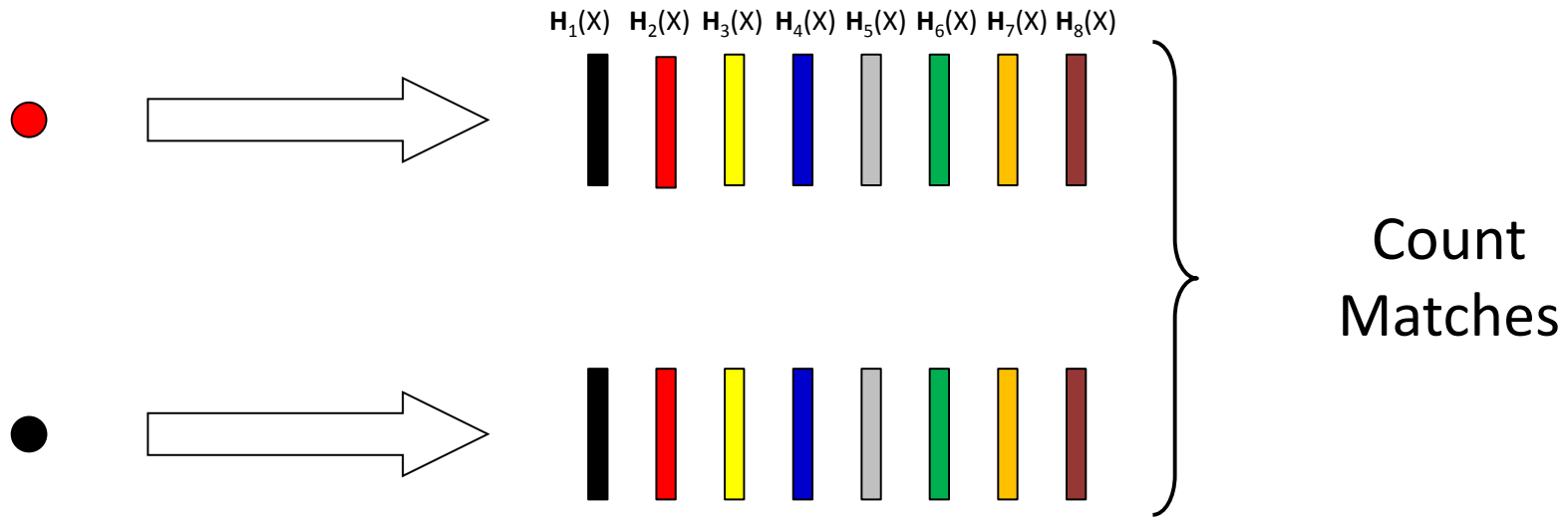


Experiments

Error on YOHO dataset (EER)

only speaker	with imposter	SVM
13.80%	**11.86%**	9.1%

What are we doing



- Estimating the distance between vectors without revealing the vectors!!

A Modified Encryption Scheme

- Conventional Encryption:
  - Each data vector is uniquely encrypted
    - Encrypted vector cannot be decrypted without key
  - Cannot compare data vectors

- A new proposal: A *weakly* private encryption scheme
  - Distance between data vectors can be determined from encrypted vectors
  - But only if they are close enough
  - ***Locality Sensitive Encryption***

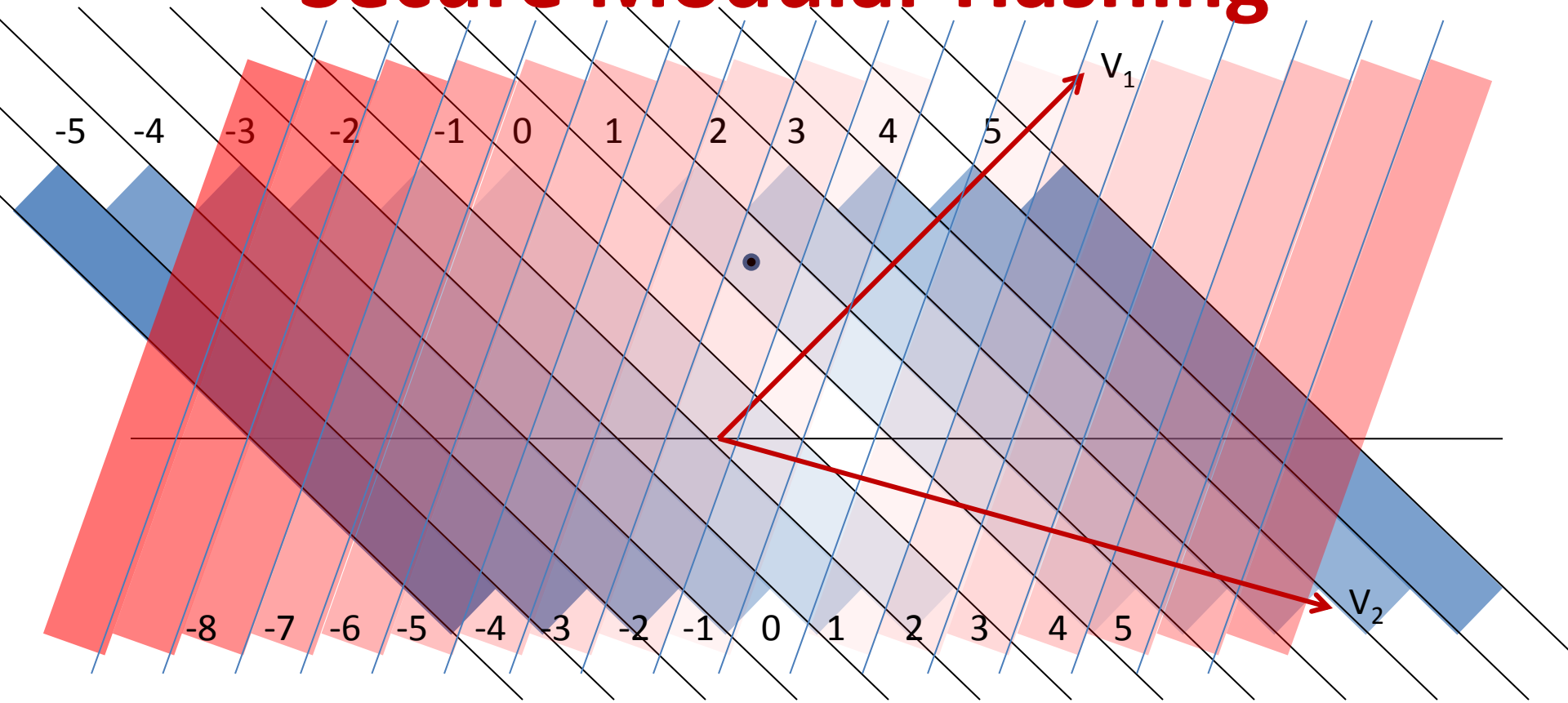
Secure Modular Hashing

$$Q_i(X) = (X^T V_i + B_i) \bmod K$$

$$\mathbf{Q}(X) = [Q_1(X), Q_2(X), \ldots, Q_M(X)]$$

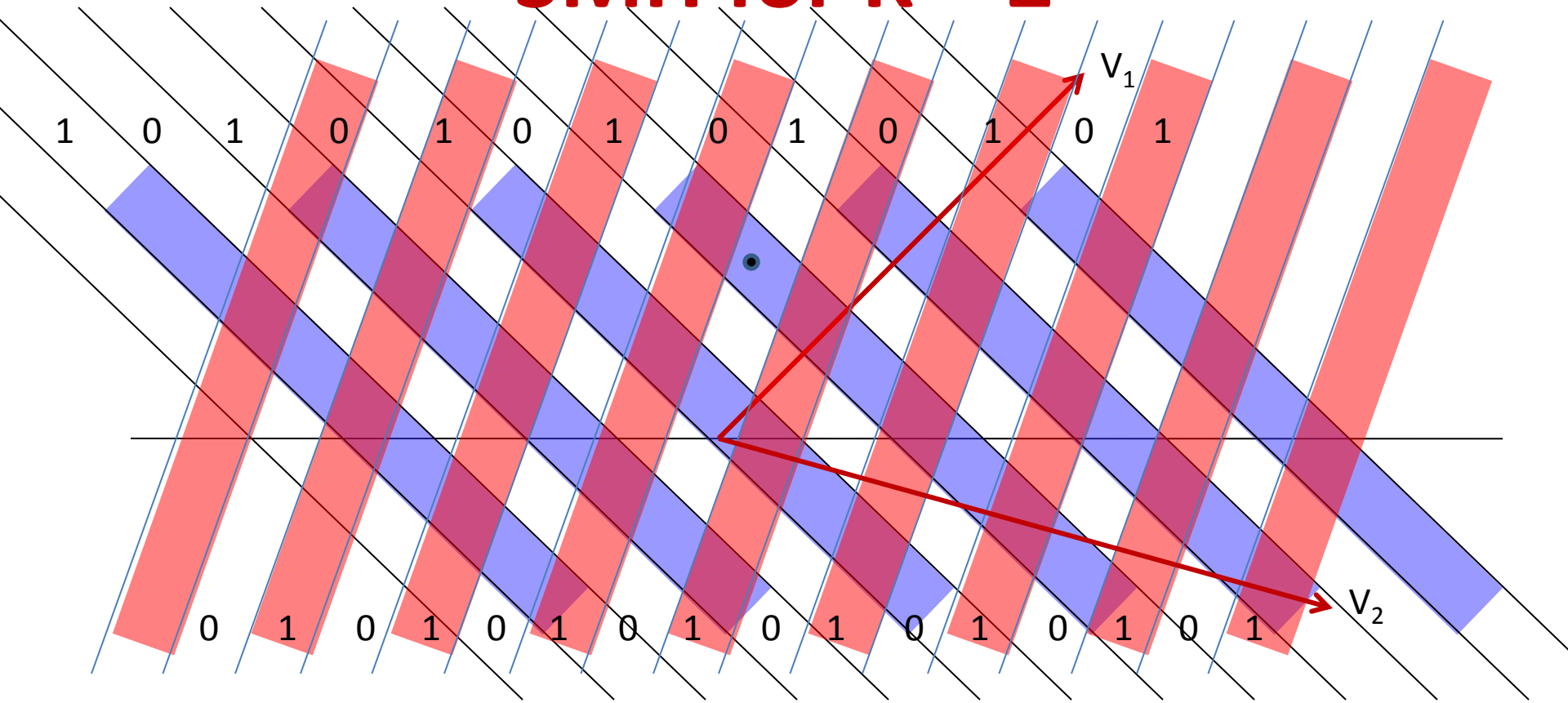
- V_i is a random Gaussian vector where each component is drawn from a Gaussian with mean 0 and variance $1/\delta$
- B_i is a random number from the uniform probability distribution $[0,\mathrm{K}]$

Secure Modular Hashing



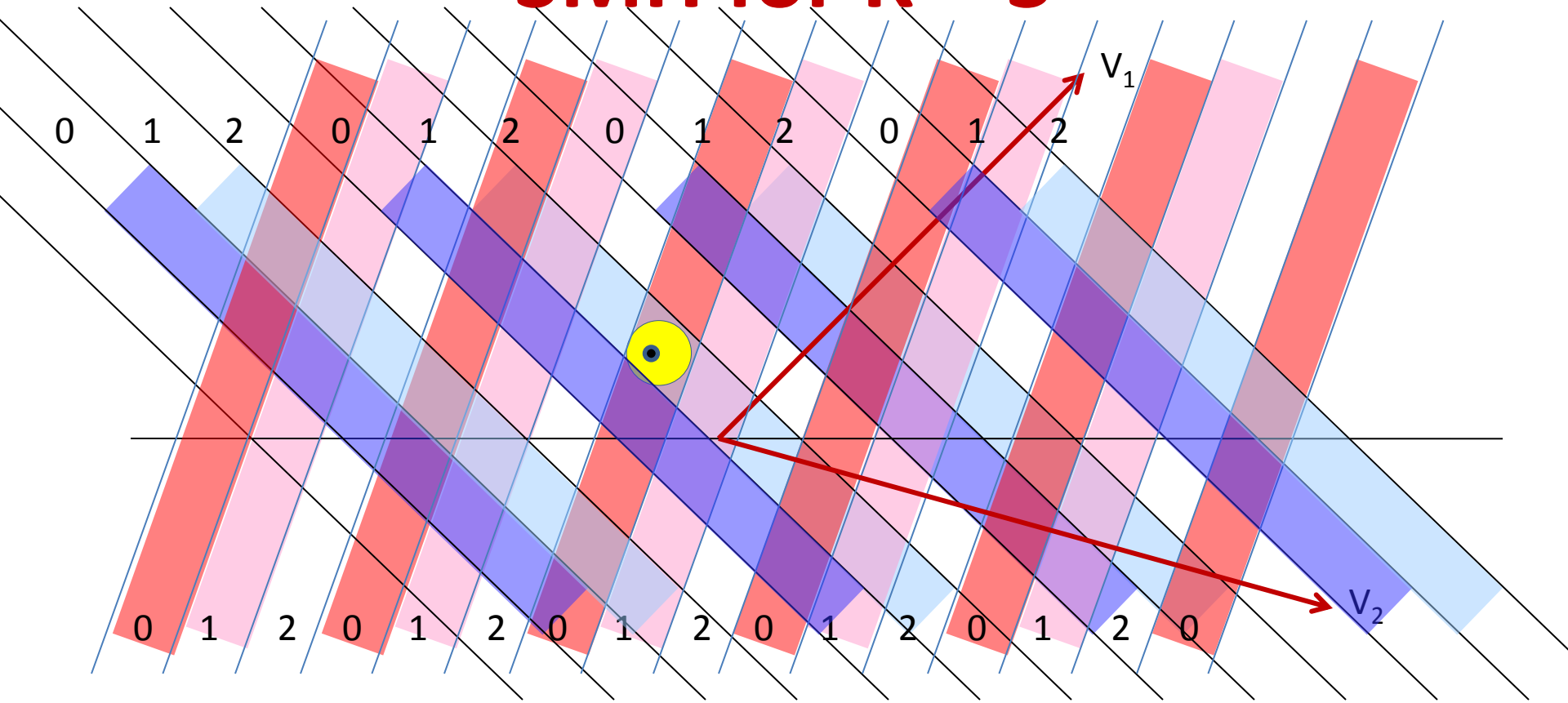
- Conventional LSH

SMH for K = 2



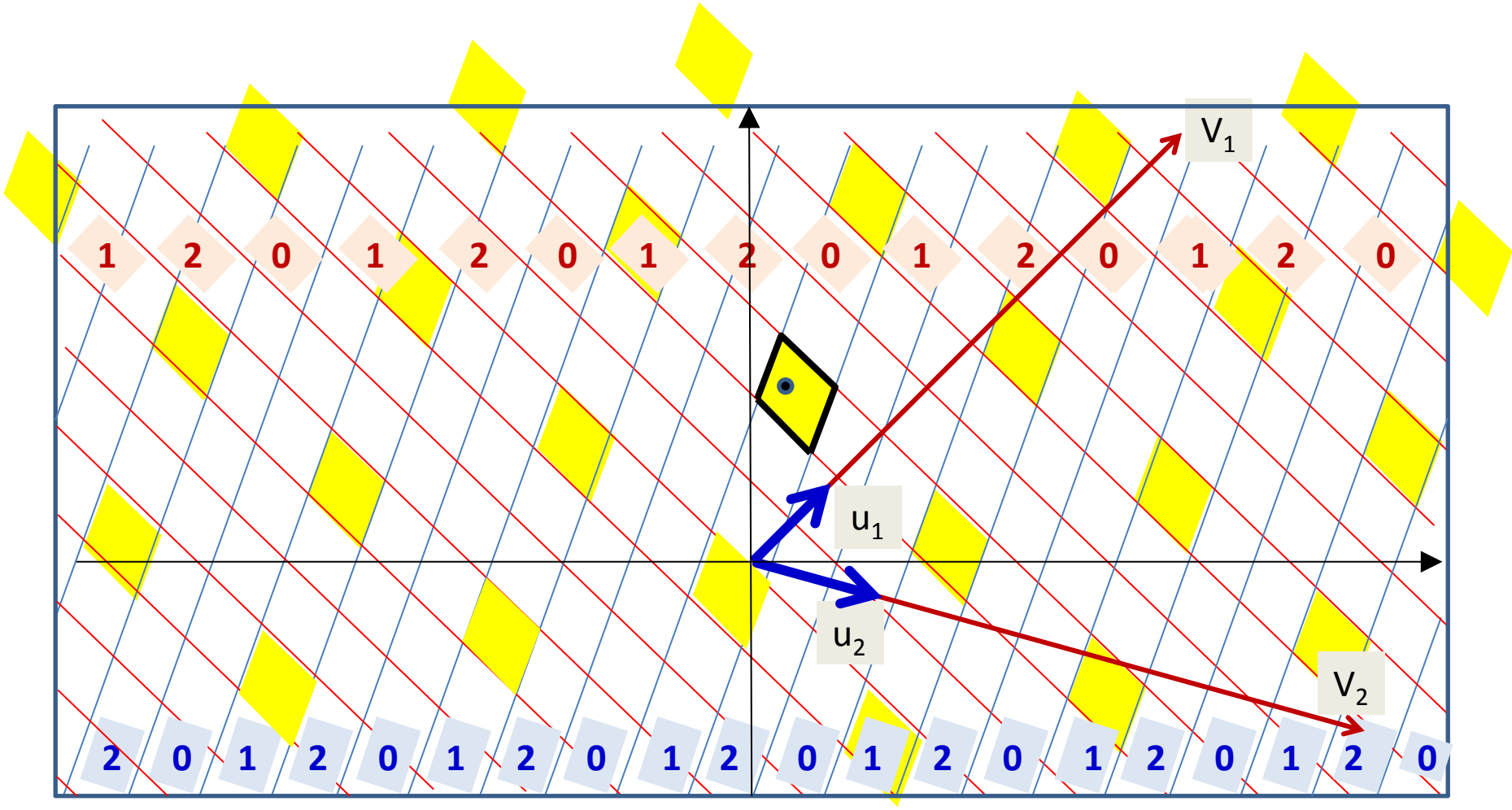
- **Solution: Banded Hashing**
  - Euclidean LSH with binary output

SMH for K = 3



- **Solution: Banded Hashing**
  - Euclidean LSH with ternary output
  - Vector is encrypted to [0 1]

All areas mapped to [0 1]



- The complete set
- Not unique

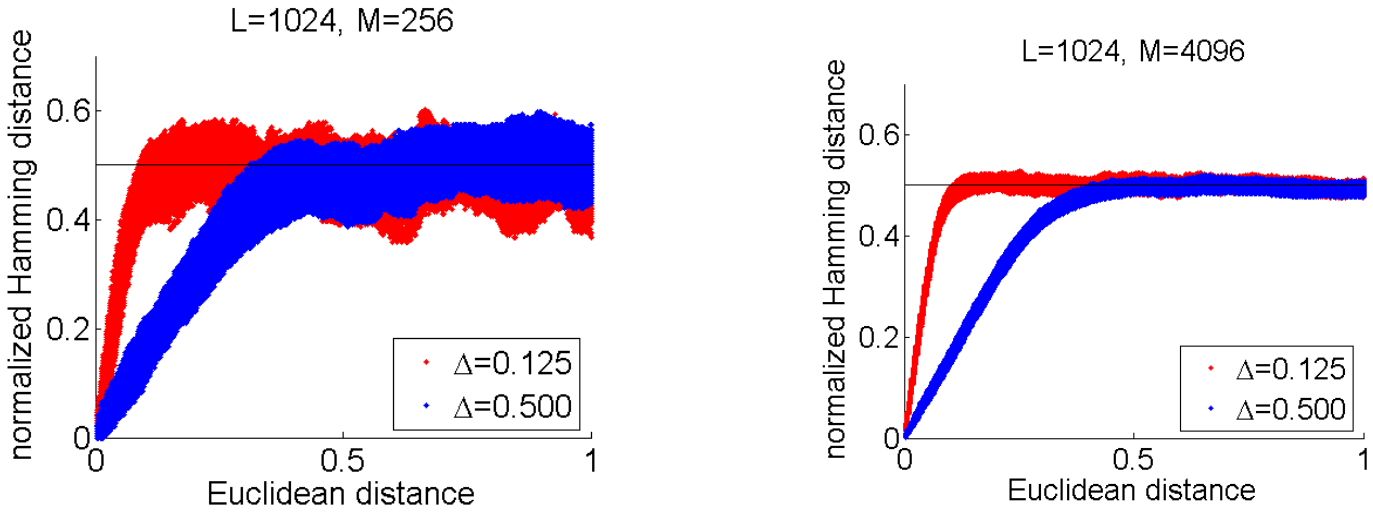
Secure Modular Hashing

$$Q_i(X) = (X^T V_i + B_i) \bmod K$$

- An interesting property
- Hamming(Q(**X**),Q(**Y**)) is proportional to d(X,Y) for d(X,Y) below a threshold
- Above the threshold it is uninformative

SMH K=2

Simulations: L-dimensional vectors, M bit hashes

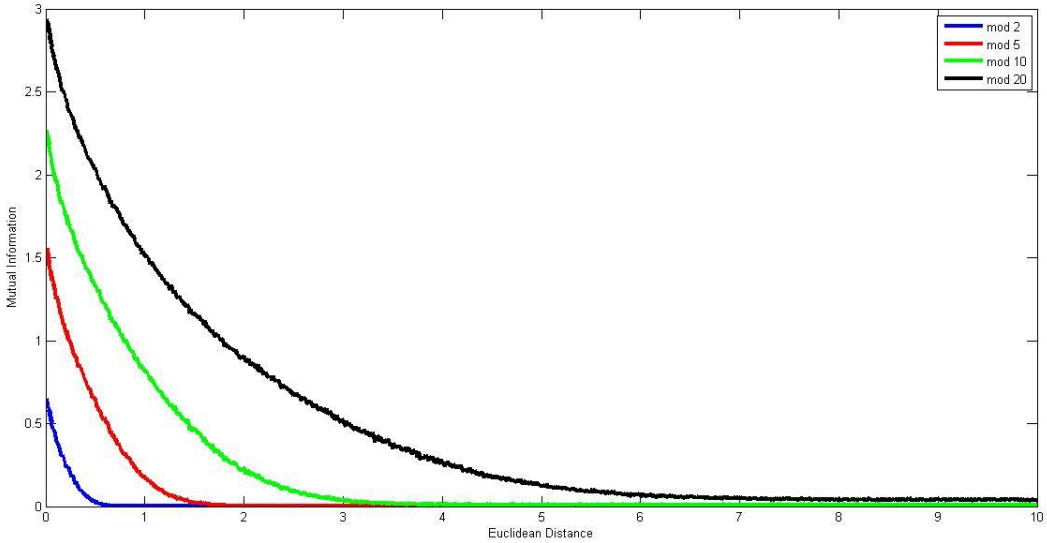


- Plot of Hamming(**Q**(X),**Q**(Y)) vs Euclidean d(X,Y) for different values of Δ, and different numbers of bits in Q(X)

We have a *local* distance measure..

- Gives you true distance, but only within a cell
- Can we use it?
- Revisit the SVM classifier..
- But first: If we're giving away the distance, is it really *secure*?

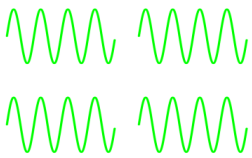
Mutual Information Between Two Vectors



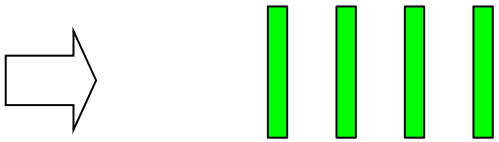
- How much does knowing the encryption of one vector tell you about the encryption of another?
- Beyond the neighbourhood of a vector, the encryption is **information theoretically secure**

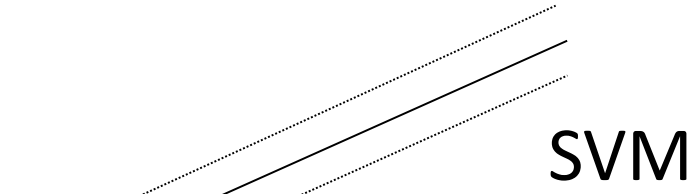
Revisiting SVM based verificaiton

Train SVM classifier across the speaker & imposter supervectors

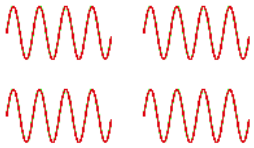


speaker

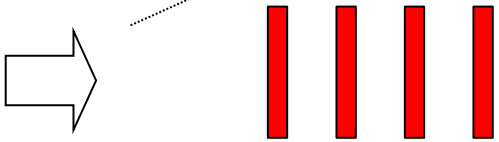




SVM



imposter



SVM with RBF Kernel

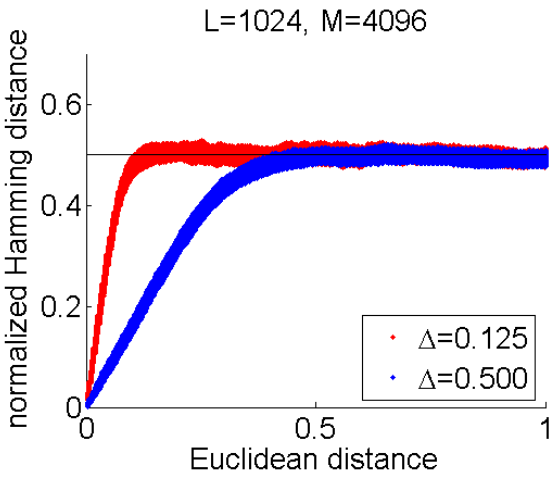
- Kernel has form:

$$K(x_1, x_2) = \exp\left(-\gamma \parallel x_1 - x_2 \parallel^2\right) = \exp\left(-\gamma d(x_1, x_2)^2\right)$$

A Hack

$$K(x_1, x_2) = \exp\left(-\gamma d(x_1, x_2)^2\right)$$

- For small $d(x_1,x_2)$:



$$d(x_1, x_2) \propto Hamm\left(Q(x_1), Q(x_2)\right)$$

- Replace $d(x_1,x_2)$ by the Hamming distance:

$$K(x_1, x_2) = \exp\left(-\beta Hamm\left(Q(x_1), Q(x_2)\right)^2\right)$$

- No longer satisfies Mercer's conditions (not a true Kernel)

SVMs with SMH

- *User* generates SMH function Q()
- User sends SMH of enrollment and imposter data
- System trains pseudo-RBF kernel SVM classifier

$$K(x_1, x_2) = \exp\left(-\beta Hamm\left(Q(x_1), Q(x_2)\right)^2\right)$$

- Verification: User sends SMH of test utterance
- System classifies it with learned pseudo-RBF kernel SVM

How it performs

#Gaussians	4	8	16	32	64	128
F-measure	76.8	89.2	92.8	94.0	94.1	94.4

SVM

Δ	13.5	14.0	14.5	15.0	15.5
bpc=4	85.4	87.9	89.0	90.9	91.6
bpc=8	90.7	92.1	93.0	93.7	93.9
bpc=16	94.0	94.0	94.6	94.6	94.9

SVM on SMH

- SMH based classification *better* than SVM performance
  - More realistically, can claim to be comparable

Import of all this

- Possible to develop authentication system with desired traits
- System never observes user's speech
  - Only obtains SMH vectors, which it cannot interpret
    - Since *User* retains hashing function Q()
- System cannot abuse user's models
  - Only works with SMH vectors generated by *User*
- System can authenticate with high accuracy

Efficiency and Security with SMH

- Efficiency:
- Data vector conversion to SMH vector
  - Insignificant time

- Distance computation with SMH vector instead of data vector
  - Actually faster!

How secure are we really?

- Information theoretic security?
  - Not entirely
  - *Local* distance still given away

- *Practical security?*
  - Absolutely
  - System never observes user's speech
  - System does not possess user's models
  - System can authenticate with high accuracy

Does it generalize?

- Proposed SMH: Encryption scheme that permits computation of *local* distances without revealing data
- Can be used to compare *any* two data vectors
- Other uses:
  - Privacy-preserving word spotting
  - Privacy-preserving important passage retrieval from documents
- Cost we pay?
  - Not reversible
  - Locally leaky
    - Given a sufficient number of samples, a hacker may map the data

Conclusion

Privacy-Preserving Speech Processing is feasible & useful

- Discussed two approaches:
  - CRYPTOGRAPHIC --- based on secure multi-party computation
  - STRING MATCHING --- based on hashing
- Cryptographic methods show theoretical feasibility
  - But practically, still infeasible
- String matching methods are practically feasible
  - For small overhead

What in the Future

- Its all in the cloud
- Sensible people will always encrypt data
- We need methods to mine/index/match/recognize encrypted data
- Have shown a couple of workable solutions, but they are not the final solution
  - Too slow
  - Too leaky

- Work on encryption schemes continues
- Alternate strategies may also be required

Thanks!

Questions?