

# Efficient Unconditionally Secure Comparison and Privacy Preserving Machine Learning Classification Protocols

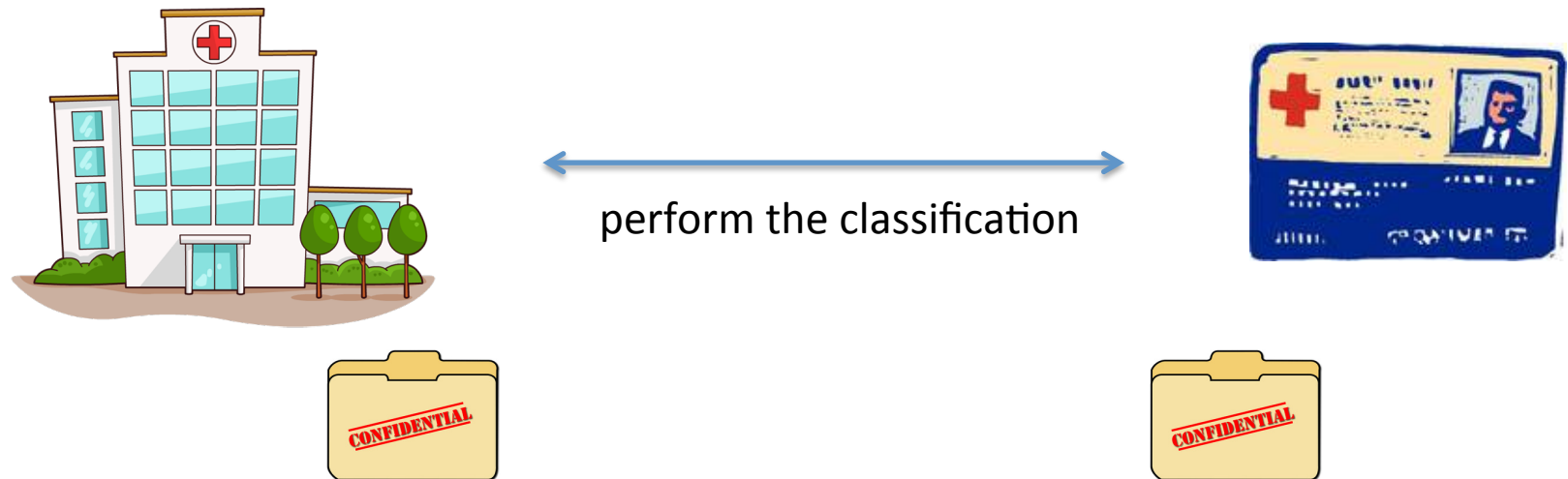
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# Problem



Both parties want to guarantee the **privacy** of their data.

Consider honest-but-curious adversaries.

# Classifiers

Hyperplane decision classifier: model  $w$  consists of  $k$  vectors  $w_1, \dots, w_k$

$$C(w, v) = \operatorname{argmax} \langle v, w_i \rangle$$

Naïve Bayes classifier: classification using maximum a posteriori decision rule and the model consists of the probability that each class happens and the probability that each input element happens in a certain class

$$C(w, v) = \operatorname{argmax} (\log \Pr(C=c_i) + \sum \log \Pr(V_j=V_j | C=c_i))$$

Building blocks:  $\operatorname{argmax}$  (comparison) and inner-product.

# Building Blocks

**Efficient** and **unconditionally secure** solutions for the building blocks.

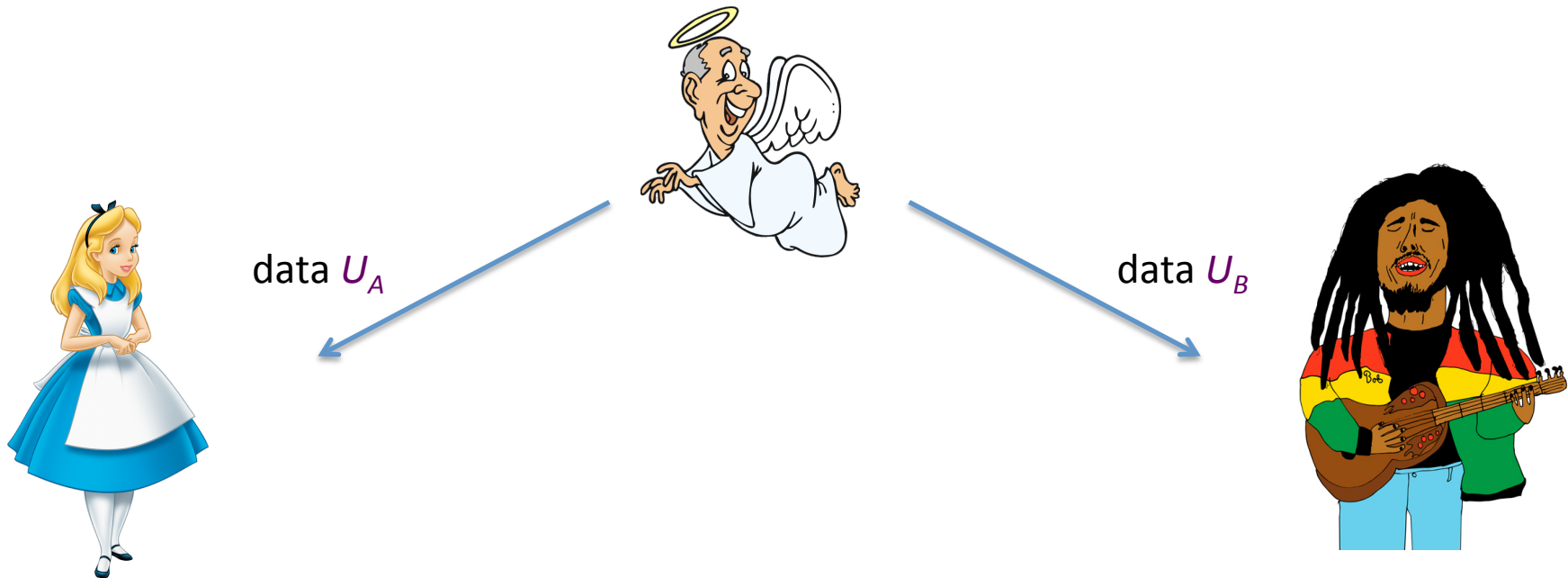
Consider the trusted initializer model.

Unconditionally secure comparisons protocols (and so argmax) can be designed using unconditionally secure multiplication as a building block.

Optimize use of the multiplication protocol.

Efficient inner-product protocol already known [DGMN11].

# Trusted Initializer Model



Trusted initializer pre-distributes **correlated randomness** to the parties.

Trusted initializer does **not** learn the inputs and does **not** participate anymore.

**Advantage:** unconditional security can be achieved with very efficient protocols.

# Computing Using Secret Shares

Use additively secret sharing (over some finite field) for performing secure computations.

For a value  $x$ , Alice receives a share  $x_A$  and Bob a share  $x_B$  such that  $x = x_A + x_B$ . Let  $[x]$  denote the secret sharing of  $x$ .

Given shares  $[x]$ ,  $[y]$  it is easy to compute shares corresponding to  $z = x + y$ ,  $z = x - y$ , or to add a/multiply by a constant.

Not so easy to compute shares for  $z = xy$  without revealing additional information.

# Multiplication Triples



random  $[s], [t], [u]$  such that  $u=st$

compute  $[m]=[x]-[s]$  and open  $m$

compute  $[n]=[y]-[t]$  and open  $n$

$$[z]=n[s]+m[t]+[u]+mn$$

Due to the blinding factors, **no** information about  $x$ ,  $y$  or  $z$  is leaked.

# Secure Comparison

For inputs of  $l$ -bits, our protocol only uses  $l$  instances of the secure multiplication.

The inputs are given as bit-wise secret sharings  $[x_i]$  and  $[y_i]$  in  $Z_q$  with  $q > 2^{l+2}$ .

The output is either  $[0]$  if  $y > x$  or  $[w]$  for a random  $w$  in  $Z_q^*$  if  $y \leq x$ .

This modified form of output is good enough for our applications.



# Secure Comparison



$[z]$  for random non-zero  $z$  and  
 $l$  multiplication triples

locally compute  $[d_i] = [x_i] - [y_i]$

locally compute  $[c_i] = [d_i] + 1 + \sum_{j=i+1}^l [d_j] 2^{l-j+2}$

compute  $[w] = [z] \prod_{i=1}^l [c_i]$

# Secure Comparison



$[z]$  for random non-zero  $z$  and  
 $l$  multiplication triples

locally compute  $[d_i] = [x_i] - [y_i]$   $d_i = -1$  and  $d_j = 0$

locally compute  $[c_i] = [d_i] + 1 + \sum_{j=i+1}^l [d_j] 2^{l-j+2}$   $c_i = 0$

compute  $[w] = [z] \prod_{i=1}^l [c_i]$

Correctness:  $y > x$  if and only if there is an  $i$  such that  $y_i > x_i$  and  $y_j = x_j$  for  $j = i+1, \dots, l$ .

# Secure Argmin

Input: bit-wise secret sharings of vectors  $v_1, \dots, v_k$



correlated data necessary for  
the underlying building blocks

compare all ordered pairs  $v_j$  and  $v_i$  to get  $[w_{i,j}]$



compute  $[p_i] = \prod_{j=1, j \neq i}^k [w_{i,j}]$



open  $p_i$  to Alice. If  $p_i \neq 0$ , she adds  $i$  to the output



# Naïve Bayes Classifier

$$C(w,v)=\operatorname{argmax} (\log \Pr(C=c_i) + \sum \log \Pr(V_j=V_j | C=c_i))$$

log of the probabilities are converted to field elements



obliviously compute the converted  $\log \Pr(V_j=V_j | C=c_i)$

use secure argmax protocol



# Hyperplane Decision Classifier

$$C(w, v) = \operatorname{argmax} \langle v, w_i \rangle$$



securely compute the inner-products [DGMN11]



convert to bit-wise secret sharings [Veu15]



use secure argmax protocol



# Recap

- ✧ Possible to obtain privacy-preserving schemes for important machine learning classifiers using as building blocks comparison, argmax and inner products.
- ✧ Optimized secure comparison protocol that fits our applications.
- ✧ Possible to eliminate the trusted initializer at the cost of having some pre-computation between the parties and losing the unconditional security.

Thank You!