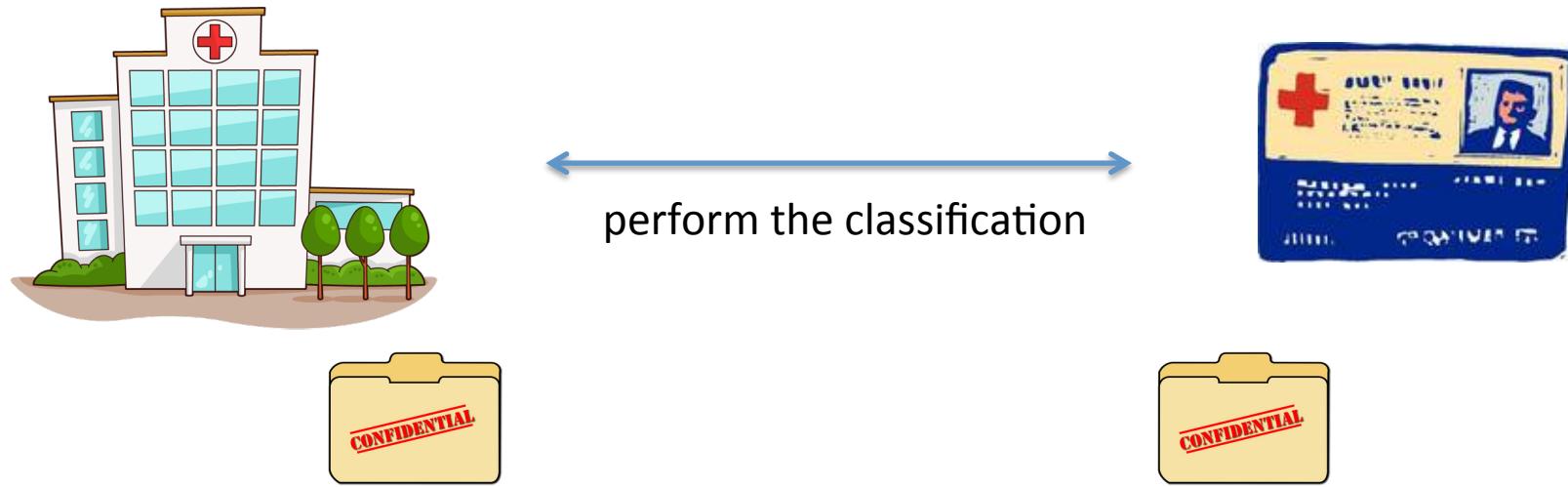


Efficient Unconditionally Secure Comparison and Privacy Preserving Machine Learning Classification Protocols

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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: argmax (comparison) and inner-product.

Building Blocks

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

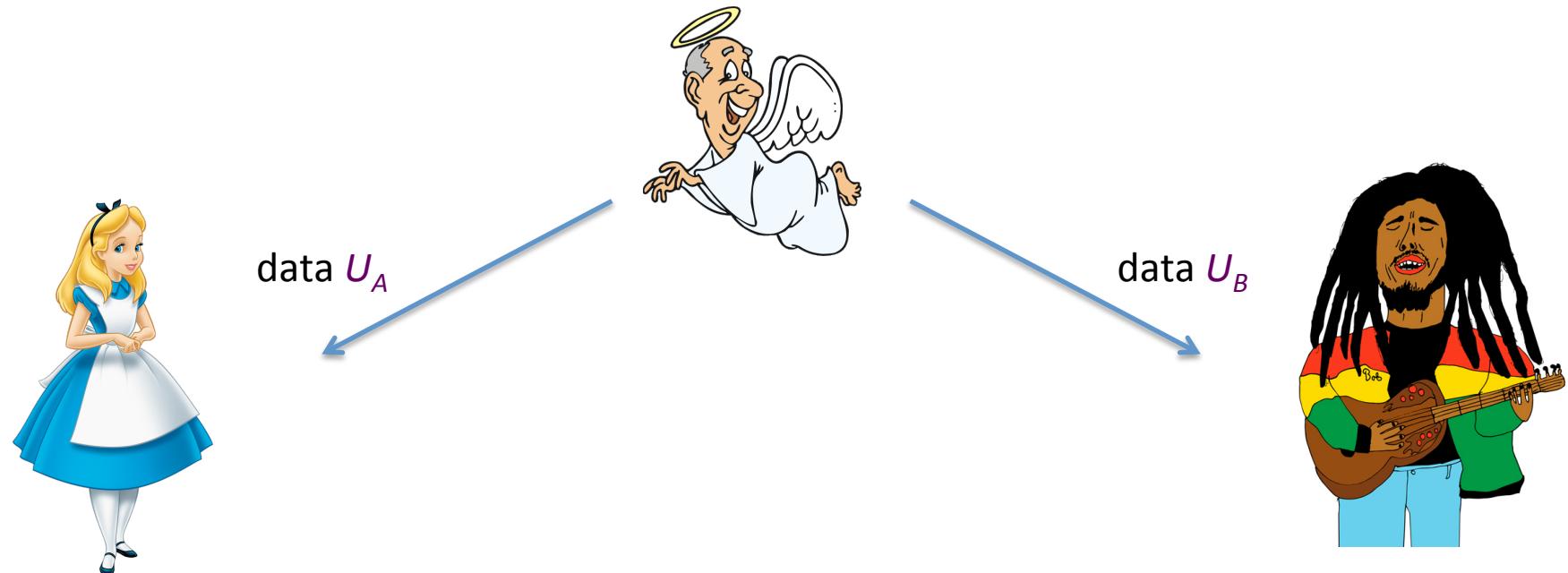
Consider the trusted initializer model.

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

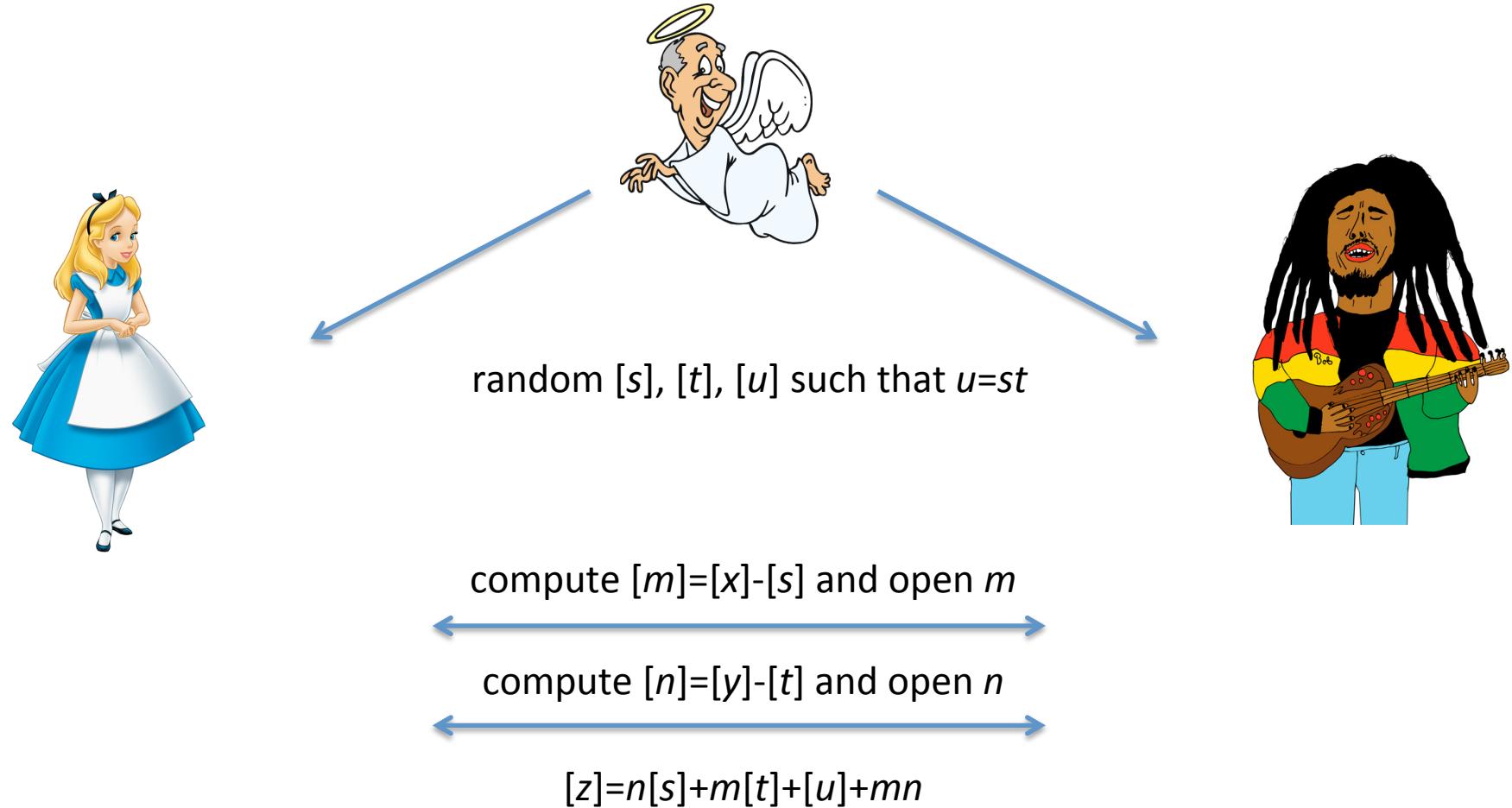
Use additively secret sharing (over some finite field) for performing secure computations.

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



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

Secure Comparison

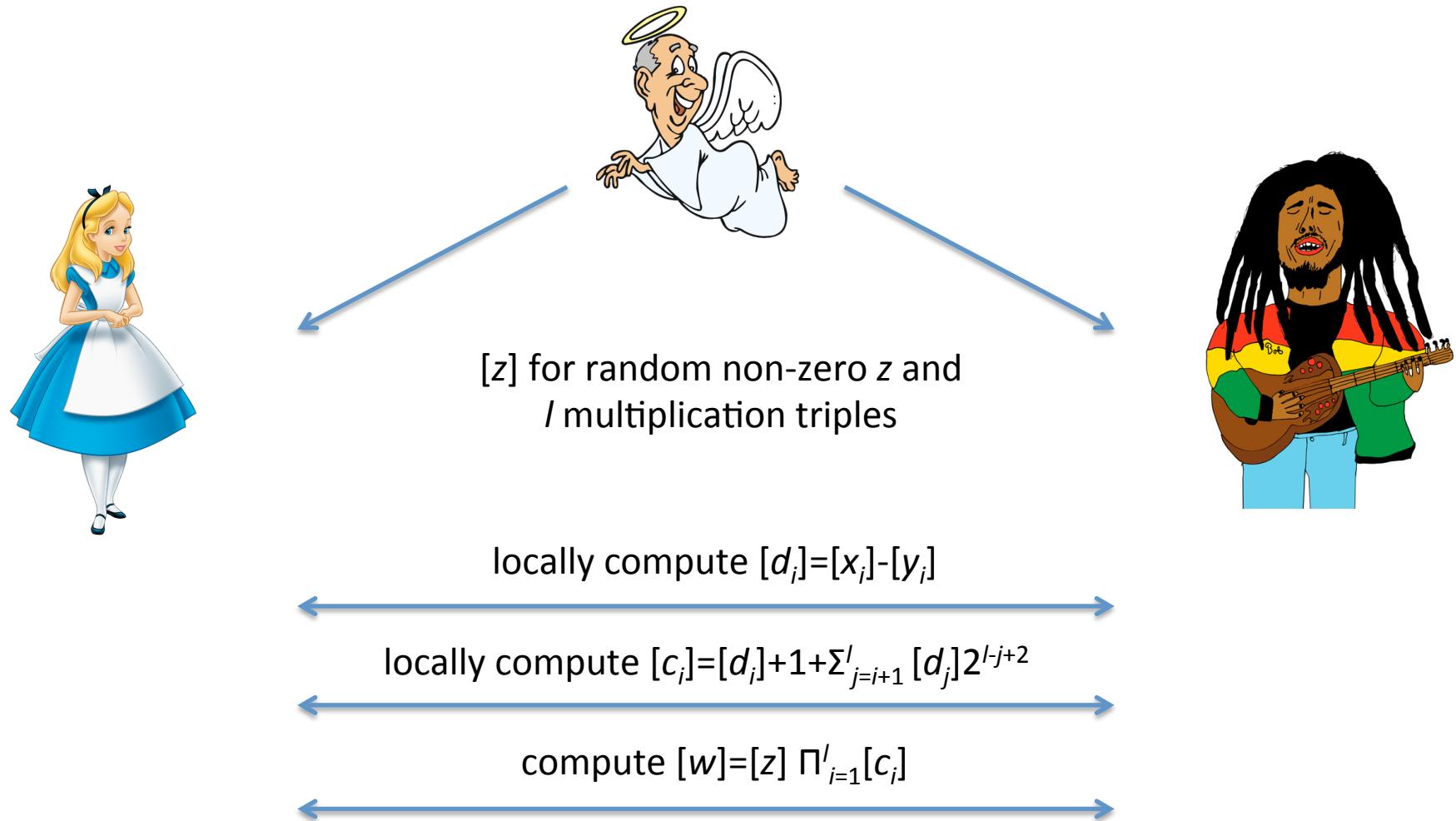
For inputs of l -bits, our protocol only uses l instances of the secure multiplication.

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

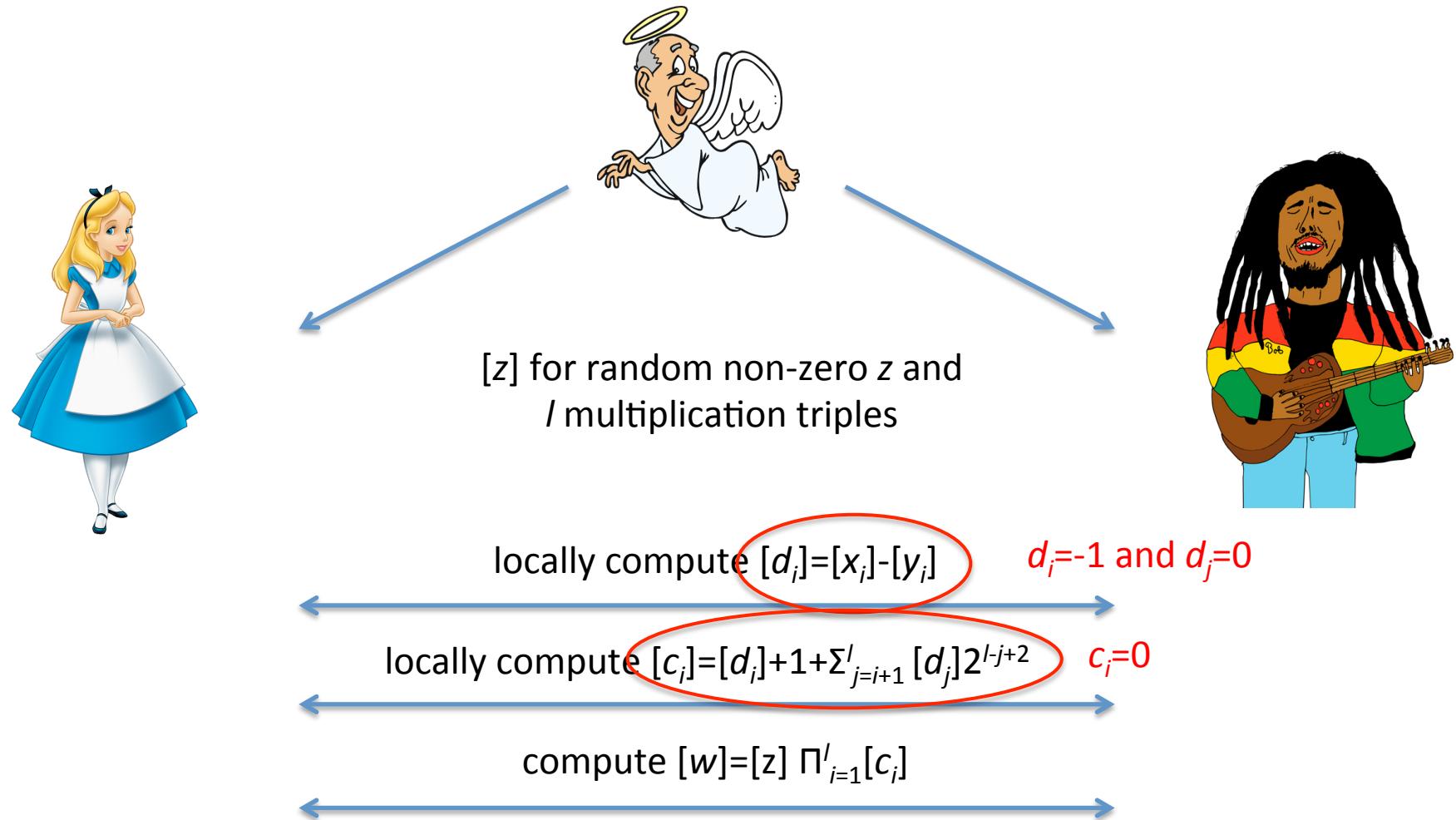
The output is either $[0]$ if $y > x$ or $[w]$ for a random w in Z_q * if $y \leq x$.

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

Secure Comparison



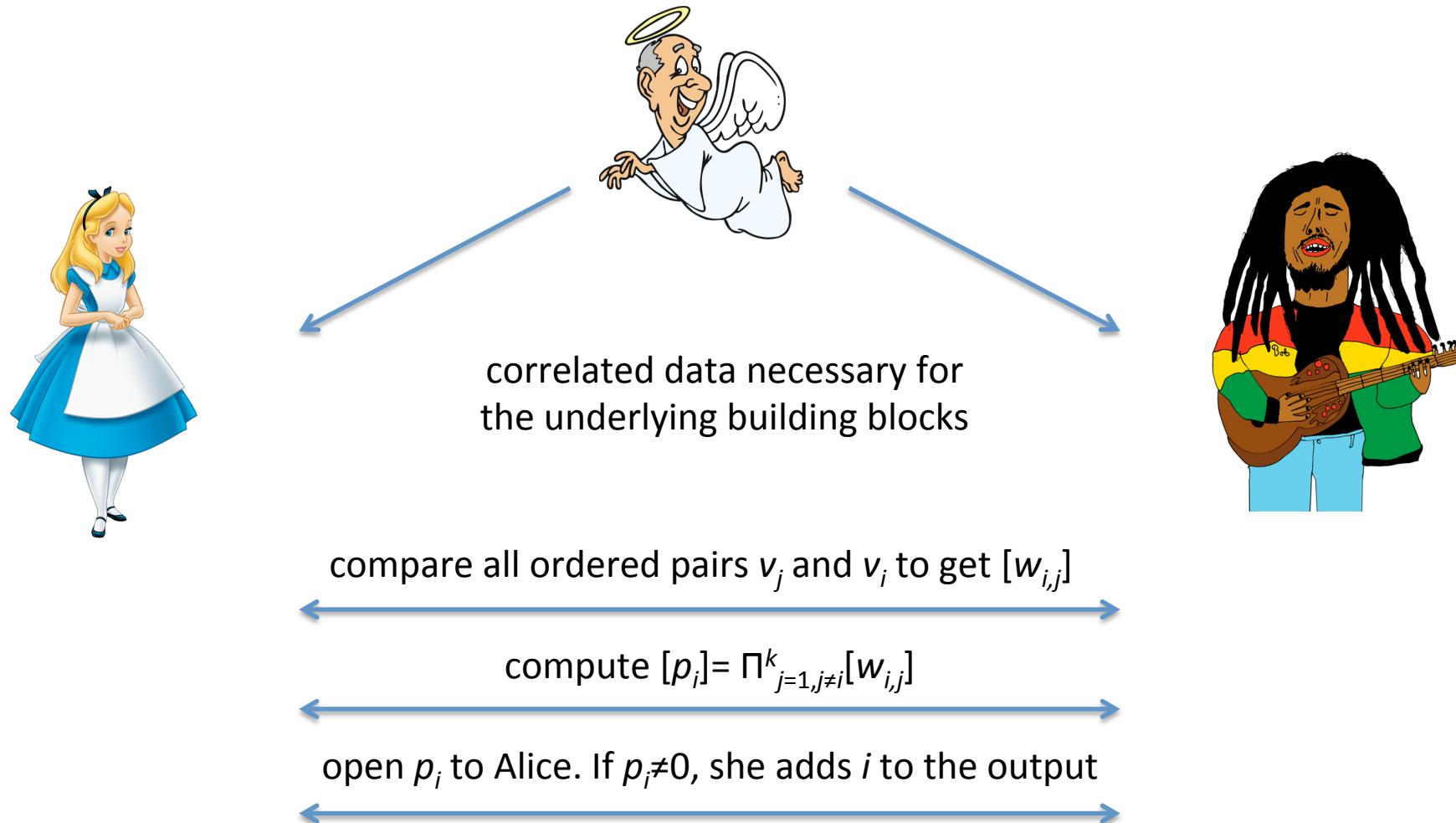
Secure Comparison



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



Naïve Bayes Classifier

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

log of the probabilities are converted to field elements



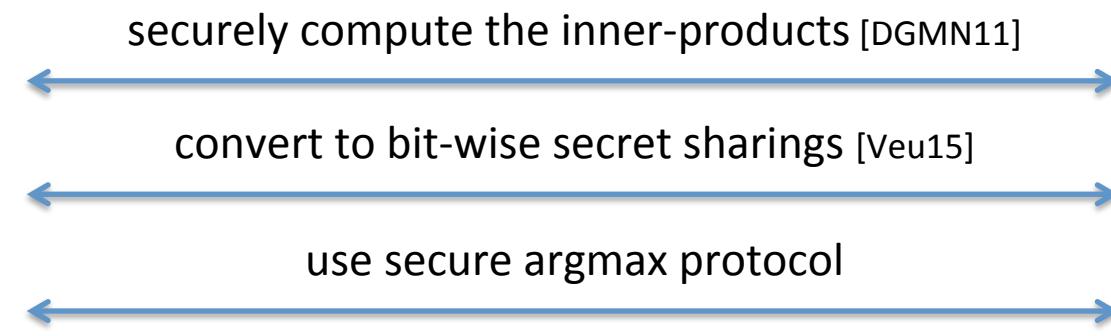
obliviously compute the converted $\log \Pr(V_j=V_j | C=c_i)$

use secure argmax protocol



Hyperplane Decision Classifier

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



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.

Танк и он!