Privately Evaluating Decision Trees and Random Forests

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Motivations



Here is my financial data:

[...]

You qualify for these deductions: [...]



classification

The Power of the Cloud

Advantage of the cloud: big data

But can now the cloud be trusted?

- Financial Records
- Medical Records
- Legal Records
- Personal Information

Privacy-Preserving Machine Learning

Leverage the power and data available in cloudbased services

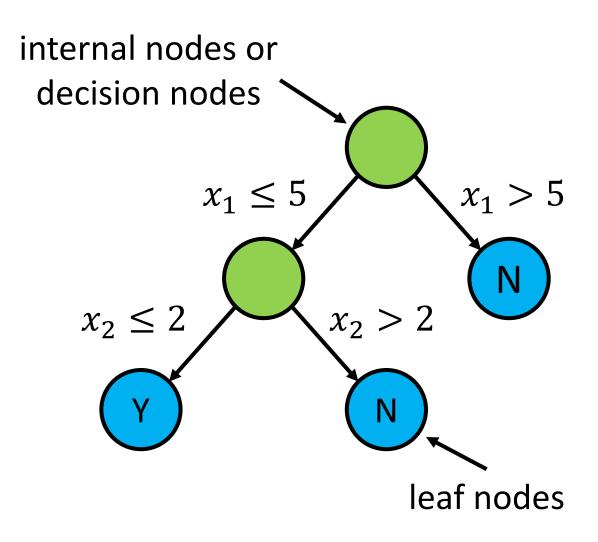
Preserve user privacy

Scope of This Talk

Consider one particular model: decision trees and their generalization, random forests

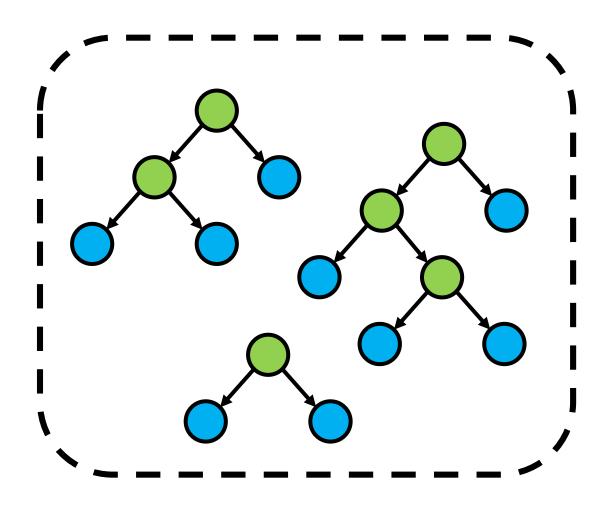
Assume that the server already has the model: focus on *private evaluation* of models

Decision Trees



- Nonlinear models for regression or classification
- Consists of a series of decision variables (tests on the feature vector)
- Evaluation corresponds to tree traversal

Random Forests



- Train many decision trees on random subsets of the features
- Output is average (majority)
 of outputs of individual
 decision trees for regression
 (classification)
- Reduces variance of model

Security Model

Semi-honest adversary: follow the protocol as written, but may try to learn additional information from the protocol trace (honest-but-curious)

Malicious adversary: can deviate arbitrarily from the protocol to satisfy its objectives

Server-Side and Client-Side Privacy

Privacy for the client: server learns no information about the client's query

Privacy for the server: client does not learn anything about the model other than what s/he already learns from the output

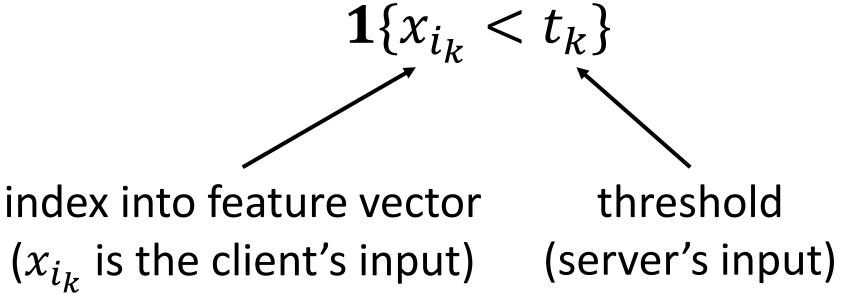
Formally, we use the real-world / ideal-world paradigm

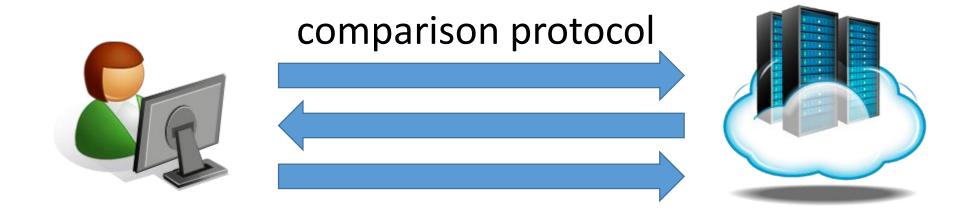
Comparison Protocol

Recall decision tree setting:

- Server has a decision tree (the model)
- Client has feature vector

Basic building block for decision trees: evaluating comparisons of the form





client input: *x*

server input: *y*

Desired functionality:

Server learns an *encryption* of comparison bit (under the client's public key), client learns nothing

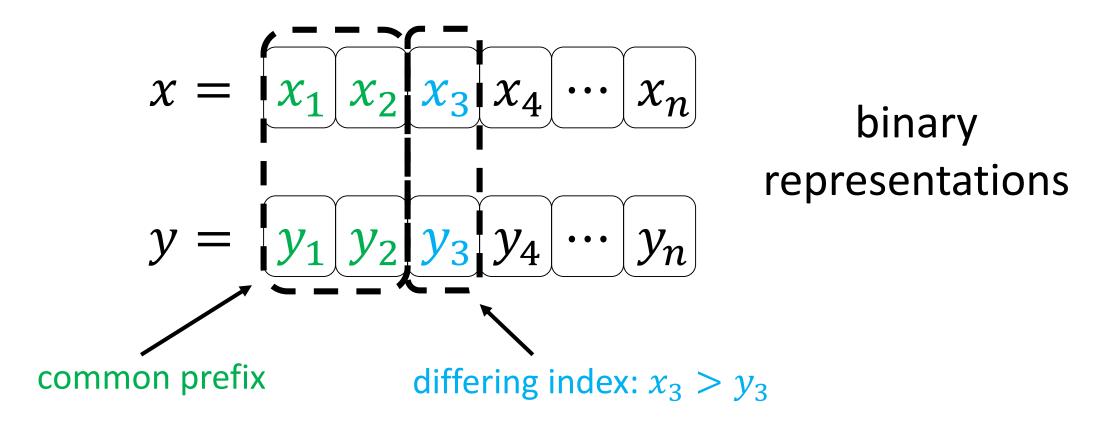
Back to the Comparison Protocol...

$$x = x_1 x_2 x_3 x_4 \cdots x_n$$

$$y = y_1 y_2 y_3 y_4 \cdots y_n$$

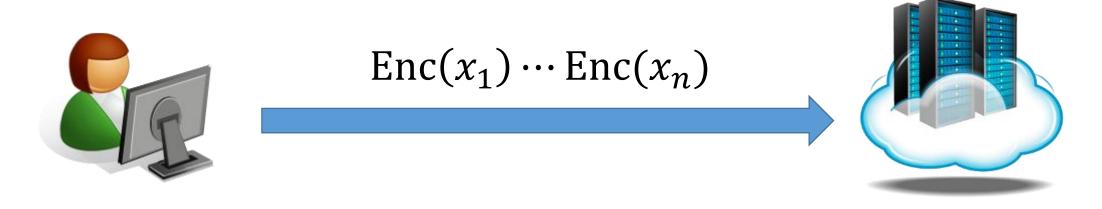
binary representations

Take two positive integers x, y and consider their binary representations



Observation:

x > y if there is an index such that $x_i > y_i$ and for all j < i, $x_j = y_j$



client input: *x* server input: *y*

Step 1: Client sends bitwise encryptions to server

Step 2: Server chooses $s \leftarrow \{-1,1\}$ and homomorphically computes



$$\operatorname{Enc}\left(x_i - y_i + s + 3\sum_{j < i} (x_j \oplus y_j)\right)$$

server input: y

Note: encryption scheme needs to be additively homomorphic

Term server computes:

$$w_{i} := \left[x_{i} - y_{i} + s \right] + \left[3 \sum_{j < i} (x_{j} \oplus y_{j}) \right]$$

If s = 1, $x_i - y_i + s = 0$ if and only if $x_i < y_i$

If s = -1, $x_i - y_i + s = 0$ if and only if $x_i > y_i$

Always non-negative, and if non-zero, then $w_i > 0$

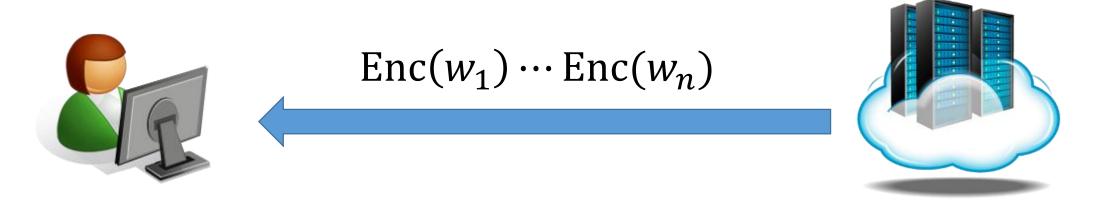
Term server computes:

$$w_i \coloneqq (x_i - y_i + s) + 3 \sum_{j < i} (x_j \oplus y_j)$$

Recall observation:

x > y if and only if there is i such that $x_i > y_i$ and for all j < i, $x_j = y_j$

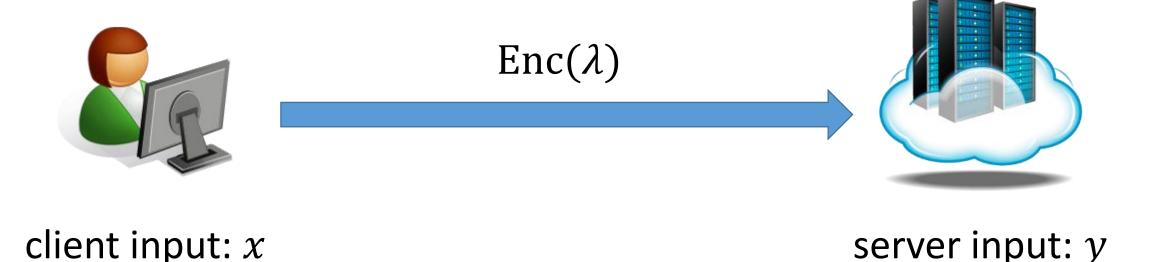
if s = -1, x > y if and only if there exists i such that $w_i = 0$ if s = 1, x < y if and only if there exists i such that $w_i = 0$



client input: *x* server input: *y*

Step 3: Server sends back $\operatorname{Enc}(w_1) \cdots \operatorname{Enc}(w_n)$

Technical detail: Server first multiplies by a random non-zero element



Step 4: Client decrypts the w_i and sends back $\operatorname{Enc}(\lambda)$ where $\lambda = 1$ only if there exists i such that $w_i = 0$ and 0 otherwise

Step 5: Given $\operatorname{Enc}(\lambda)$ and s, server can compute result of comparison: $\operatorname{Enc}(\mathbf{1}\{x < y\})$.



server input: *y*

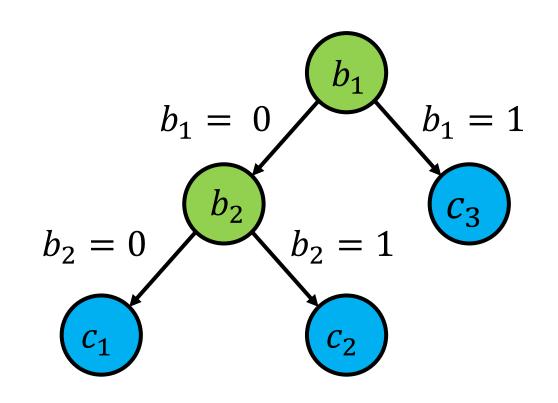
Recall:

if s = -1, x > y if and only if there exists i such that $w_i = 0$ if s = 1, x < y if and only if there exists i such that $w_i = 0$

Semi-honest Secure Protocol

Key Idea: suppose we give the client b_1 , b_2 , and the structure of the tree

Then, client can compute the *index* of the outcome



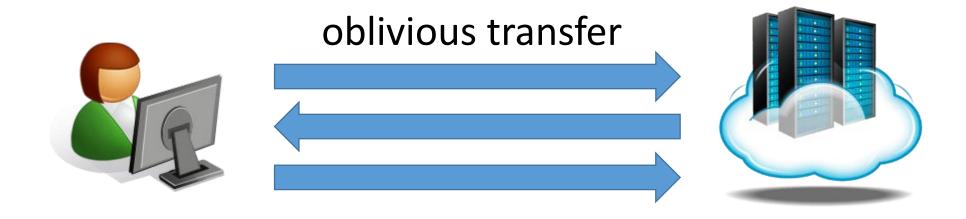
Problem: Leaks the structure of the tree!

Semi-honest Secure Protocol

Suppose client knew the index of the outcome

Problem reduces to well-studied problem: oblivious transfer

Oblivious Transfer (OT)



client's input: index *i*

server's input: database $\{m_1, ..., m_n\}$

Desired functionality:

Client learns m_i and nothing else, server learns nothing

Semi-honest Secure Protocol

Suppose client knew the index of the outcome

Problem reduces to OT: treat leaves as database, client knows index

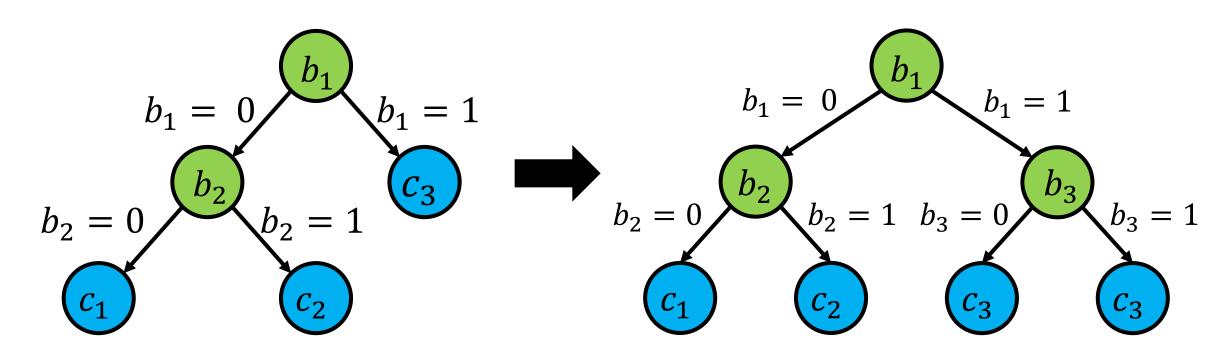
Problem: Need to hide structure!

 $\begin{array}{c|c} & b_2 & c_3 \\ \hline & c_2 & \\ \hline & & \\ \end{array}$ $\begin{array}{c|c} & c_2 & \\ \hline & & \\ \end{array}$ $\begin{array}{c|c} & c_3 & \\ \hline & & \\ \end{array}$

leaves become OT database

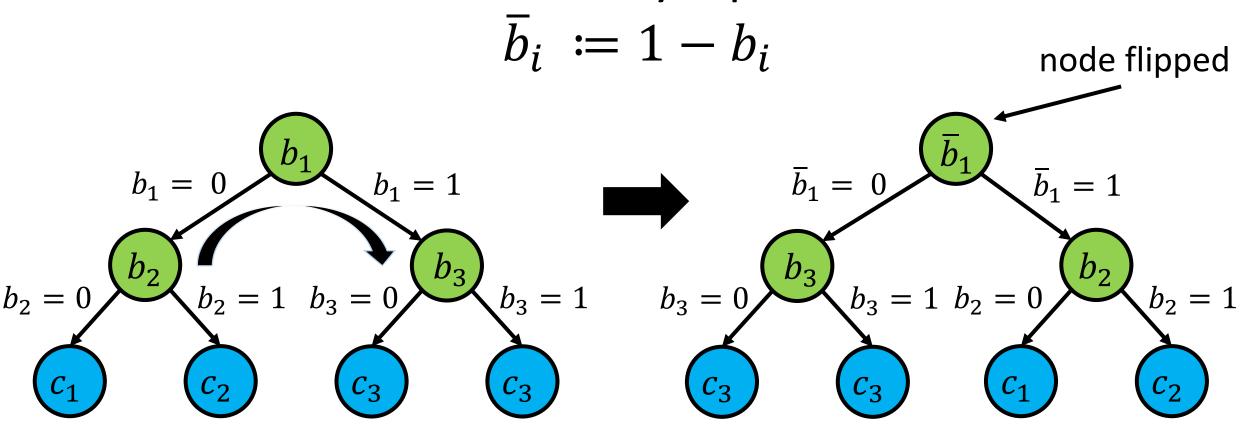
Hiding the Structure

1. Padding: Insert "dummy" nodes to obtain complete tree



Hiding the Structure

2. Randomization: Randomly flip decision variables:



Hiding the Structure: Randomization

Choose

$$s = s_1 s_2 \dots s_m \leftarrow \{0,1\}^m$$

uniformly at random

If
$$s_i = 1$$
 then flip

$$b_i \mapsto 1 - b_i$$

Semi-honest Secure Protocol

- 1. Server: Pad and randomize the decision tree
- 2. Server & Client: Engage in comparison protocol to compute each b_i
- **3. Client:** Compute the index *j* of the leaf node
- **4.** Client & Server: Engage in OT to obtain c_j

Theorem. This protocol is secure against *semi-honest* adversaries.

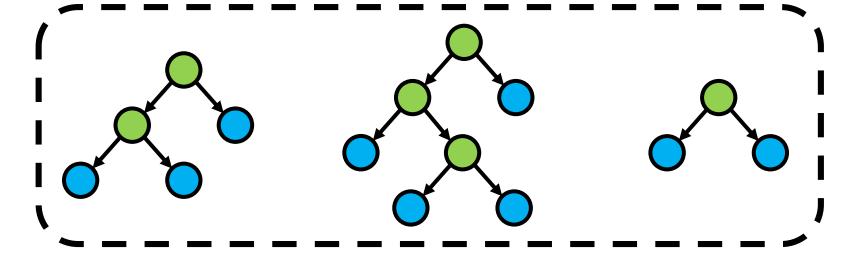
From Trees to Forests

Naïve Solution: Evaluate each tree independently using the protocol

Problem: Reveals more information about the model than just the classification

From Trees to Forests

Better Solution: Use an additive secret-sharing to hide intermediate results

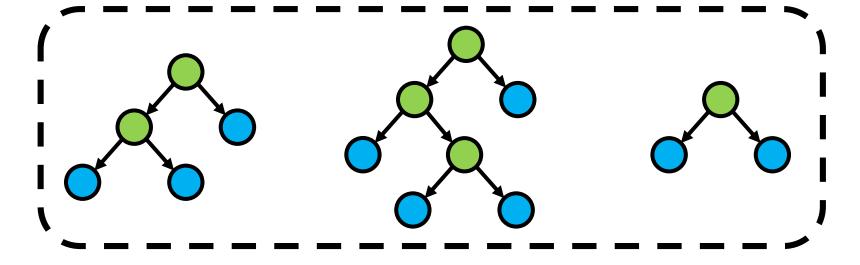


Evaluate each tree as before, but each individual evaluation now looks random

add r_1 to each add r_2 to each add r_3 to each classification classification

From Trees to Forests

Better Solution: Use an additive secret-sharing to hide intermediate results



Reveal $\sum_i r_i$ to the client, which allows client to learn sum (mean) of predicted values

add r_1 to each add r_2 to each add r_3 to each classification

classification classification

Implementation

Implementation

Implemented private decision tree + random forest protocol (semi-honest security)

Two primary components:

- Comparison protocol
- Oblivious Transfer

Implementation

Comparison protocol instantiated with exponential variant of ElGamal encryption

Fast instantiation using elliptic curves
Oblivious transfer based on Naor-Pinkas with OT Extensions

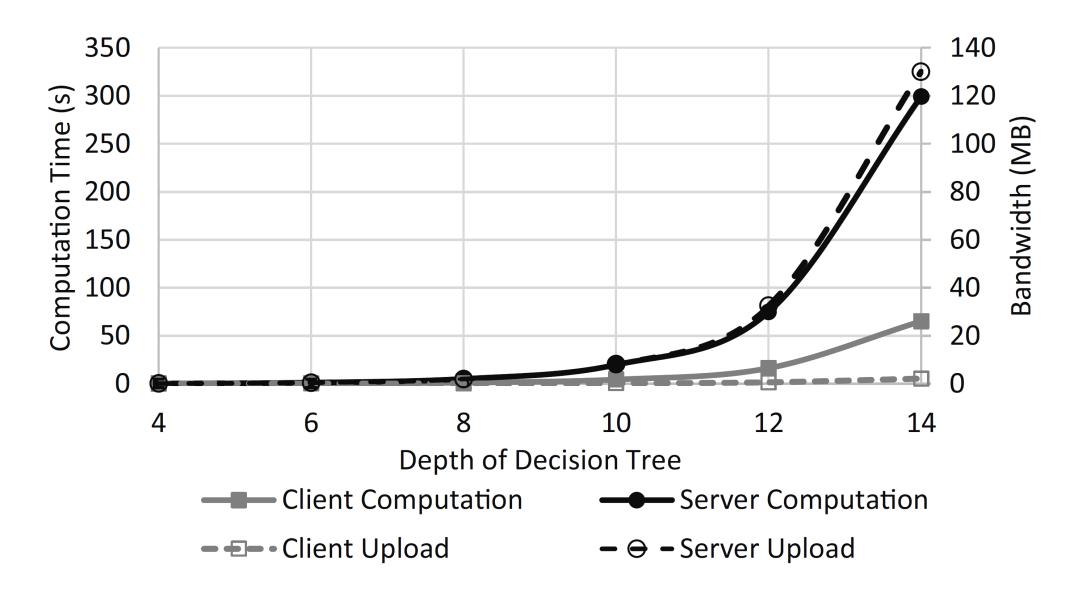
Decision Tree Evaluation on ECG Data

	Security Level	Computation (s)		Bandwidth (KB)
		Client	Server	Danuwiuth (ND)
[BFK+09]	80	1.765	4.235	112.2
[BPGT14]	80	1.485	2.595	4272
This work	128	0.091	0.188	101.9

Experimental Parameters:

- Data Dimension: 6
- Depth of Decision Tree: 4
- Number of Comparisons: 6

Performance for Complete Decision Trees



One-Sided Security (Malicious Model)

Privacy of the server's model is ensured against a malicious client

Privacy of the client's input is ensured against a malicious server

However, client not guaranteed to receive "correct" answer

Extensions to One-Sided Security

Possible attacks on semi-honest protocol:

- **1. Server:** Pad and randomize the decision tree
- 2. Server & Client: Engage in comparison protocol to compute each b_i
- **3. Client:** Compute the index *j* of the leaf node containing the response
- 4. Client & Server: Engage in OT to obtain c_j

Client might cheat during comparison protocol (for example, encrypt a value that is not 0/1)

Solution: zero-knowledge proofs

Client might cheat by requesting a different index

Solution: "conditional" oblivious transfer

Conclusion

Simple protocols for decision tree evaluation in both semihonest and malicious setting

Semi-honest decision tree / random forest evaluation protocols are fairly practical