Doing Machine Learning Blindfolded

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i-like.org.uk

Outline

1. Introduction
   - Motivation
   - High-level overview of homomorphic encryption
   - Discussion of constraints
2. Software
   - Discussion of implementation issues and `HomomorphicEncryption` R package.
3. Encrypted Machine Learning
   - Completely Random Forests (CRF)
   - Extreme variant of extremely random forests
   - Including 'stochastic fraction estimator'
   - Embarrasingly parallel down to single datum
4. Other / Future Work
   - Brief discussion of other complete and in progress projects

Introduction

Motivation

Security in statistics and machine learning applications is a growing concern:

- computing in a 'hostile' environment (e.g. cloud computing);
- donation of sensitive/personal data (e.g. medical/genetic studies);
- complex models on constrained devices (e.g. smart watches)
- running confidential algorithms on confidential data (e.g. engineering reliability)

Encryption the solution?

Encryption can provide security guarantees …

Easy

$$\texttt{Enc}(k_p, m) \rightleftharpoons c \qquad\qquad \texttt{Dec}(k_s, c) = m$$

Hard without k_s

… but is typically ‘brittle’.

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$$m_1 \qquad m_2 \xrightarrow{+} m_1 + m_2$$

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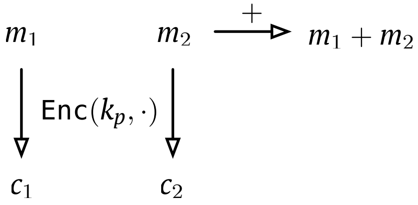

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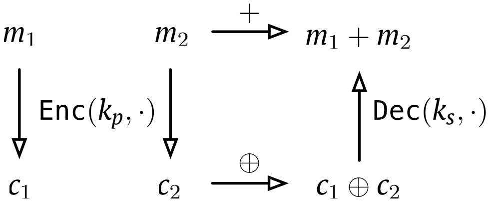

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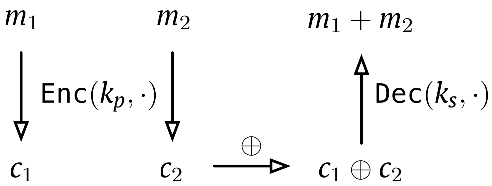

Formal definition

Definition (Homomorphic encryption scheme)

An encryption scheme is said to be *homomorphic* if there is a set of operations $\circ \in \mathcal{F}_M$ acting in message space, M, that have corresponding operations $\diamond \in \mathcal{F}_C$ acting in cipher text space, C, satisfying the property:

$$\mathtt{Dec}(k_s, \mathtt{Enc}(k_p, m_1) \diamond \mathtt{Enc}(k_p, m_2)) = m_1 \circ m_2 \quad \forall\, m_1, m_2 \in M$$

A scheme is *fully homomorphic* if $\mathcal{F}_M = \{+, \times\}$ and an arbitrary number of such operations are possible.

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A scheme is *fully homomorphic* if $\mathcal{F}_M = \{+, \times\}$ and an arbitrary number of such operations are possible.

$\{+, \times\}$ pretty limiting? Note that if $M = \mathrm{GF}(2)$, then:

- $+ \equiv \veebar$, i.e. XOR, 'exclusive or'
- $\times \equiv \wedge$, i.e. AND, 'and'

Moreover, *any* electronic logic gate can be constructed using only XOR and AND gates.

Limitations of homomorphic encryption

1. Message space (what we can encrypt)
   - Commonly only easy to encrypt binary/integers/polynomials
2. Cipher text size (the result of encryption)
   - Present schemes all inflate the size of data substantially (e.g. 1MB $\rightarrow$ 16.4GB)
3. Computational cost (computing without decrypting)
   - 1000's additions per sec
   - $\approx$ 50 multiplications per sec
4. Division and comparison operations (equality/inequality checks)
   - Not possible in current schemes!
5. Depth of operations
   - After a certain depth of multiplications, need to 'refresh' cipher text: hugely time consuming, so avoid!

We really are doing statistics blindfolded ...

Software

HomomorphicEncryption R package (Aslett 2014)

All core code in high-performance multi-threaded C++, but accessible via simple R functions and overloaded operators:

```
library("HomomorphicEncryption")

p <- pars("FandV")
k <- keygen(p)
c1 <- enc(k$pk, c(42,34))
c2 <- enc(k$pk, c(7,5))
cres1 <- c1 + c2
cres2 <- c1 * c2
cres3 <- c1 %*% c2
dec(k$sk, cres1)
dec(k$sk, cres2)
dec(k$sk, cres3)
```

Demo

Encrypted Machine Learning

Statistics & Machine Learning Encrypted?

Lots of constraints! Are traditional statistics and machine learning techniques out of reach to run on encrypted data?

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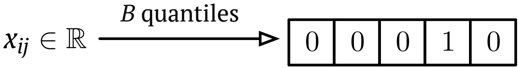
So, want to build a random forest on encrypted data … but,

- No comparisons possible to evaluate splits
- No max possible to find highest class vote
- No division possible to do average votes
- …

Thus random forests (and other methods) need to be tailored for encrypted computation. This is where statistics and machine learning community can get involved!

Completely Random Forests (CRFs) — Data encoding

1



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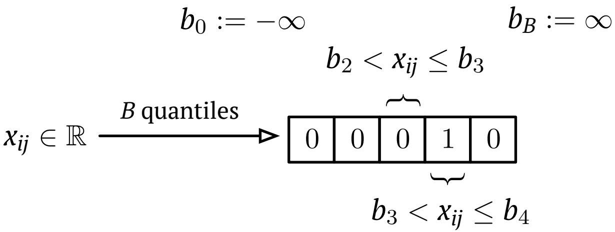

Completely Random Forests (CRFs) — Data encoding

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$$b_0 := -\infty \qquad b_B := \infty$$

$$b_2 < x_{ij} \leq b_3$$

$$x_{ij} \in \mathbb{R} \xrightarrow{B \text{ quantiles}} \boxed{0}\boxed{0}\boxed{0}\boxed{1}\boxed{0} = \{x_{ijk} : k = 1, \dots, B\}$$

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2. Then,

$$\mathbb{I}(x_{ij} \leq b_l) = \sum_{k=1}^{l} x_{ijk} \quad \text{and} \quad \mathbb{I}(x_{ij} > b_l) = \sum_{k=l+1}^{B} x_{ijk}$$

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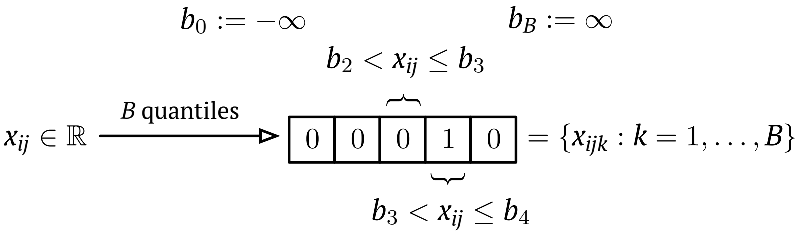

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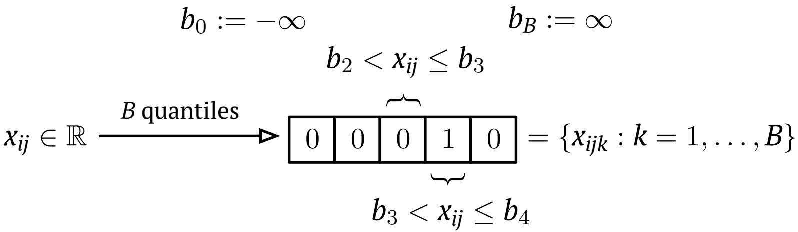
1. 

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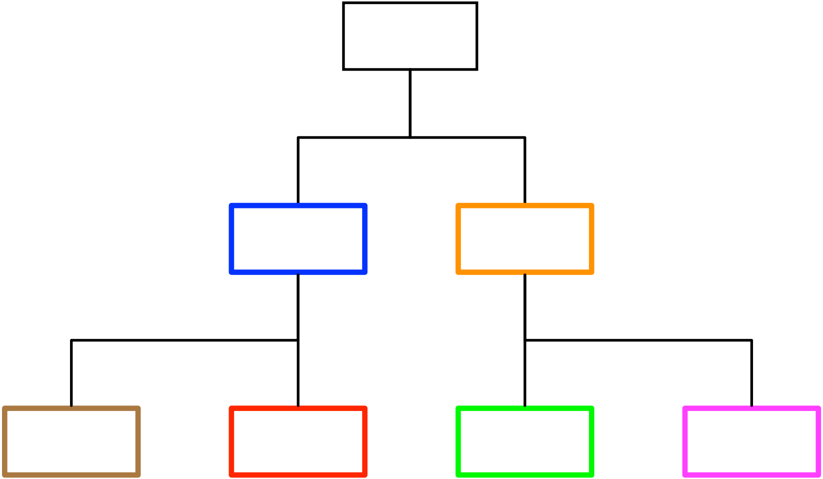
3. Similarly encode response category c, $y_i \to y_{ic} \in \{0, 1\}$.
4. Build a decision tree selecting variable j and split point b_l *completely* at random to a fixed depth.

CRFs — Tree 'fitting', I



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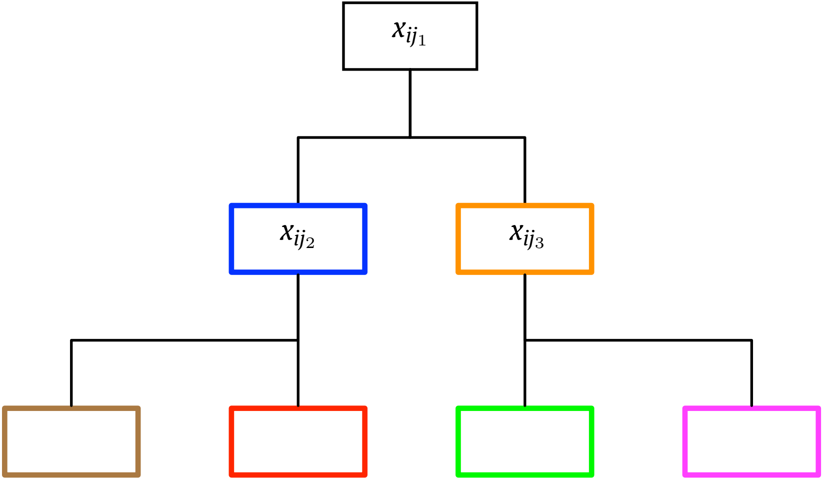

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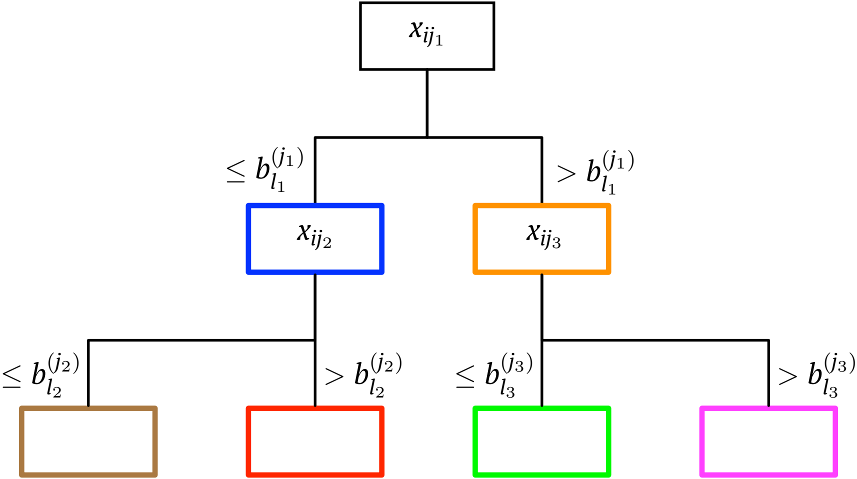

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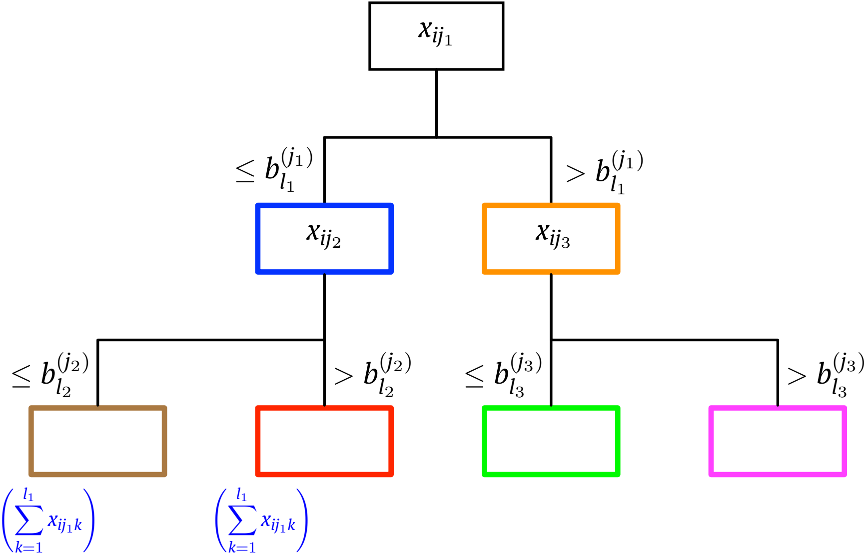

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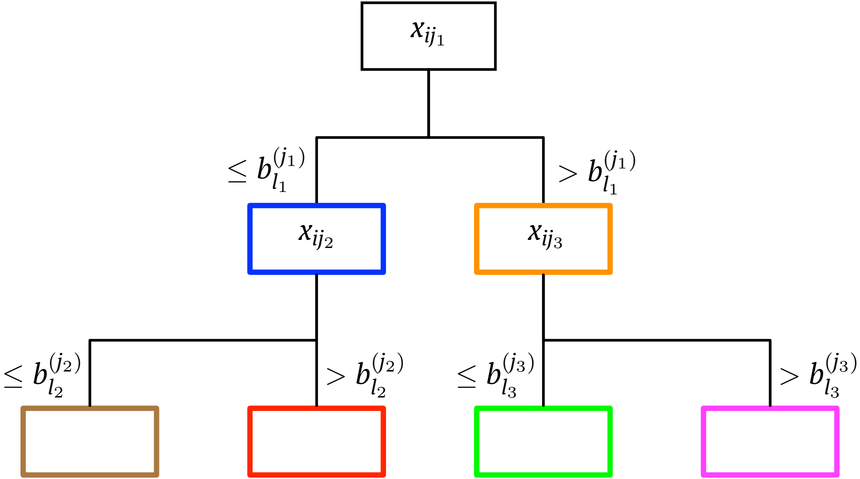
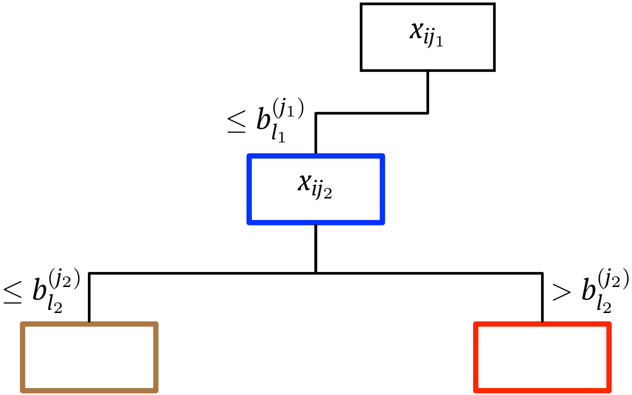


$\left(\sum_{k=1}^{l_1} x_{ij_1k}\right)\left(\sum_{k=1}^{l_2} x_{ij_2k}\right)$ $\left(\sum_{k=1}^{l_1} x_{ij_1k}\right)\left(\sum_{k=l_2+1}^{B} x_{ij_2k}\right)$

Exactly one terminal leaf indicator evaluates to 1, encrypted.

CRFs — Tree ‘fitting’, II



$$\left(\sum_{k=1}^{l_1} x_{ij_1k}\right)\left(\sum_{k=1}^{l_2} x_{ij_2k}\right) \qquad \left(\sum_{k=1}^{l_1} x_{ij_1k}\right)\left(\sum_{k=l_2+1}^{B} x_{ij_2k}\right)$$

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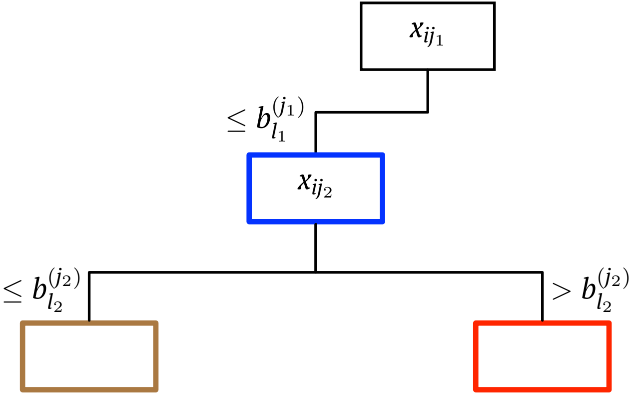

$$\nu_{ic} = y_{ic} \left(\sum_{k=1}^{l_1} x_{ij_1 k} \right) \left(\sum_{k=1}^{l_2} x_{ij_2 k} \right) \qquad \nu_{ic} = y_{ic} \left(\sum_{k=1}^{l_1} x_{ij_1 k} \right) \left(\sum_{k=l_2+1}^{B} x_{ij_2 k} \right)$$

NB Must evaluate *all* branches and categories as blindfold.

CRFs — Prediction

Prediction involves:

- evaluating a new observation through all branches;
- taking product with corresponding vote totals for each class;
- summing across trees and across leaves to get total votes for each class.

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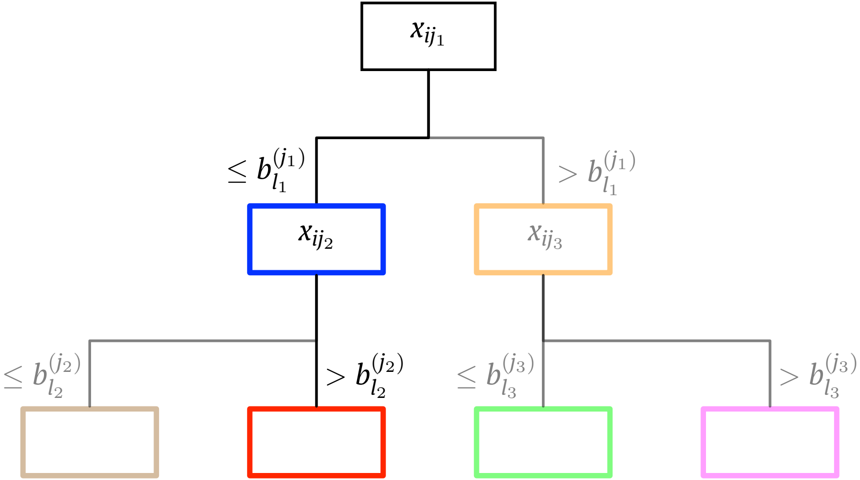
Random Forests usually use:

1. single vote per tree (requires comparison to find max)
2. relative class frequencies (requires division and $[0, 1]$ value)

But here trees contribute raw 'vote' totals to the prediction: confused leaves with many votes can overwhealm certain ones with few.

CRFs — Raw votes problem



class	A	B	C
votes, $\sum_i \nu_{ic}$	78	7	15

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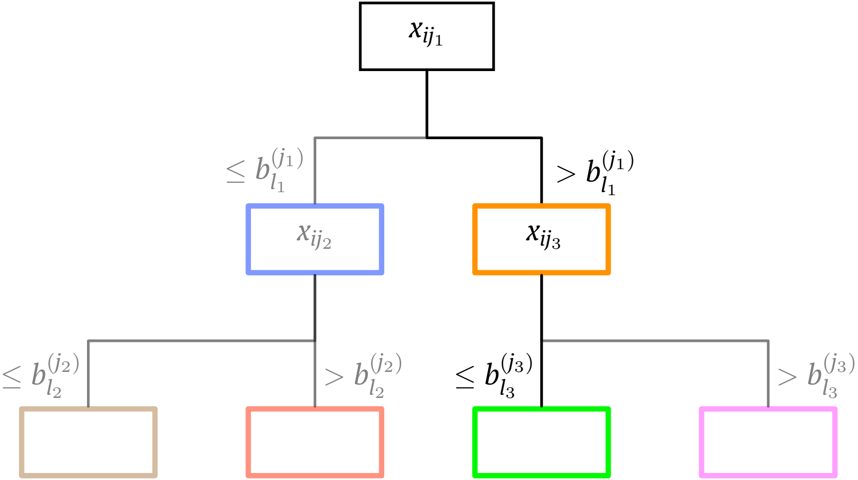
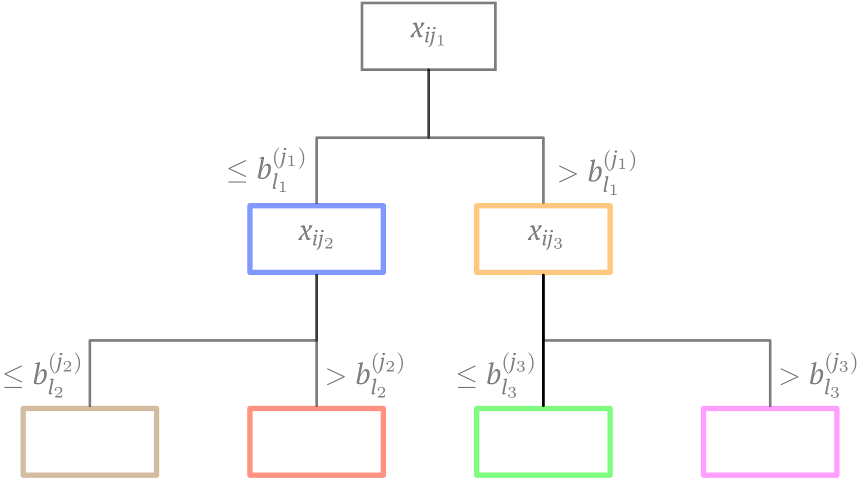


class	A	B	C
votes, $\sum_i \nu_{ic}$	1007	1080	1015

CRFs — Raw votes problem



class	A	B	C
$\Rightarrow$ overall votes, $\sum_i \nu_{ic}$	1085	1087	1030

Relative class frequencies

Let ν_c be the number of votes for class c in a leaf. The relative class frequency contribution should be:

$$\frac{\nu_c}{\sum_c \nu_c}$$

But, this belongs to $[0, 1]$ which we can't represent and involves division.

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But, this belongs to $[0, 1]$ which we can't represent and involves division.Target equivalently:

$$\nu_c \left\lfloor \frac{N}{\sum_c \nu_c} \right\rceil$$

where N is the number of training observations.

- By construction $\sum_c \nu_c \leq N$, so $0 \leq \frac{\sum_c \nu_c}{N} \leq 1$
- Recall, $X \sim \text{Geometric}(p) \implies \mathbb{E}[X] = p^{-1}$

Stochastic fraction estimate (I)

Thus, an unbiased approximation to fraction is draw from Geometric distribution with probability $\frac{\sum_c \nu_c}{N}$.
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Crucial observation: $\nu_c := \sum_{i=1}^N \nu_{ic}$ where $\nu_{ic} \in \{0, 1\} \; \forall \, i, c$.

(recall ν_{ic} is 1 if training obs. i was of class c and fell in this leaf of the decision tree … leaf indices supressed)

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$\implies$ blind sampling with replacement from $\{\sum_c \nu_{ci} : i = 1, \dots, N\}$ will produce an encrypted 1 with probability exactly $\frac{\sum_c \nu_c}{N}$.

$\implies$ can blind sample the latent bernoulli process underlying a Geometric$\left(p = \frac{\sum_c \nu_c}{N}\right)$ random variable.

Stochastic fraction estimate (II)

New problem! count number of leading zeros in an encrypted Bernoulli process.

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Inspiration from CPU hardware algorithm for renormalising the mantissa of an IEEE floating point number.

Let $\xi_1, \dots, \xi_M$ be a resampled vector ($\xi_i = \sum_c \eta_{cj}$, some j) and assume M is a power of 2.

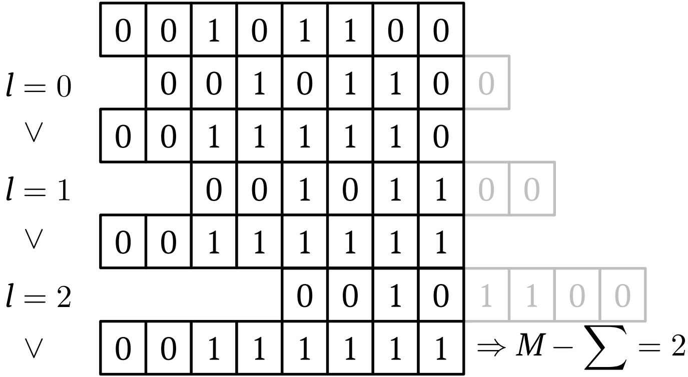
1. For $l \in \{0, \dots, \log_2(M) - 1\}$:
   - Set $\xi_i = \xi_i \vee \xi_{i-2^l} = \xi_i + \xi_{i-2^l} - \xi_i \xi_{i-2^l} \quad \forall\, 2^l + 1 \leq i \leq M$
2. The number of leading zeros is $M - \sum_{i=1}^M \xi_i$

Corresponds to increasing power of 2 bit-shifts OR'd with itself, all computable encrypted.

$$\implies \left\lfloor \frac{N}{\sum_c \nu_c} \right\rceil \approx M - \sum_{i=1}^{M} \xi_i + 1$$

Stochastic fraction estimate (III)

CPU hardware algorithm for mantissa normalisation



Stochastic fraction estimate (IV)

Bias
Clearly, since blindfolded can't sample *until* a 1 observed, so choose a fixed M and accept small bias.

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The shrinkage is mild unless there are fewer than $\frac{N}{M}$ observations in the leaf, in which case the shrinkage is more extreme: this is desirable because it shrinks the influence of underpopulated leaves.
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Computational consideration
Multiplicative depth of this algorithm is M, which must be factored into tree building.

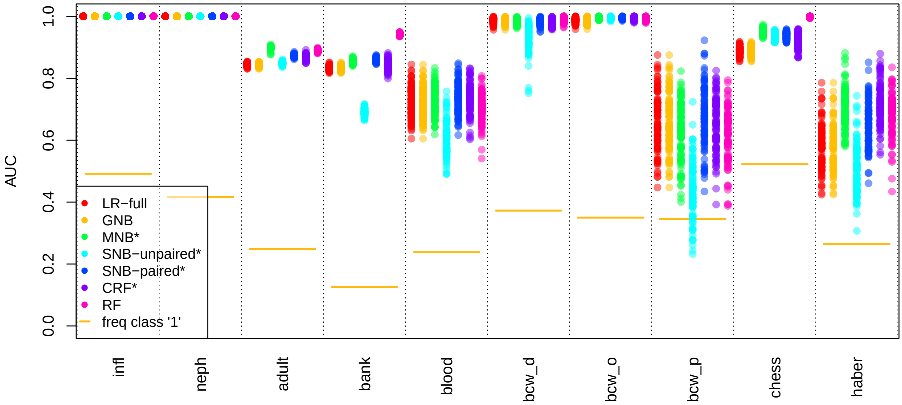
Theoretical homomorphic scheme requirements

To build a forest of trees with L levels, the homomorphic encryption scheme must support:

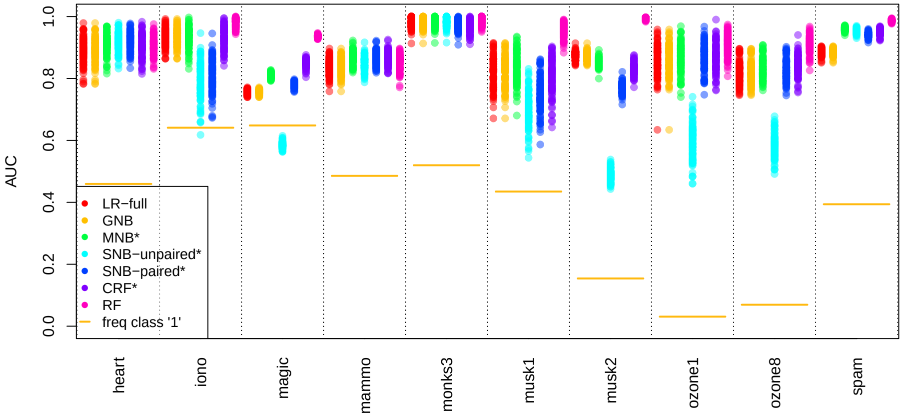
- depth L multiplications for tree building
- depth $L + M$ for stochastic fraction adjustment
- depth $2L + M$ for building, adjustment and prediction.

Furthermore, for the current generation of Ring Learning With Errors encryption schemes where the message space is a polynomial ring, it must support coefficients up to $T \max\{\sum_i y_{ic} : c = 1, \ldots, |\mathcal{C}|\}$.

Results (I)


AUC
0.0
0.2
0.4
0.6
0.8
1.0
LR−full
GNB
MNB*
SNB−unpaired*
SNB−paired*
CRF*
RF
freq class '1'
infl
neph
adult
bank
blood
bcw_d
bcw_o
bcw_p
chess
haber

Results (II)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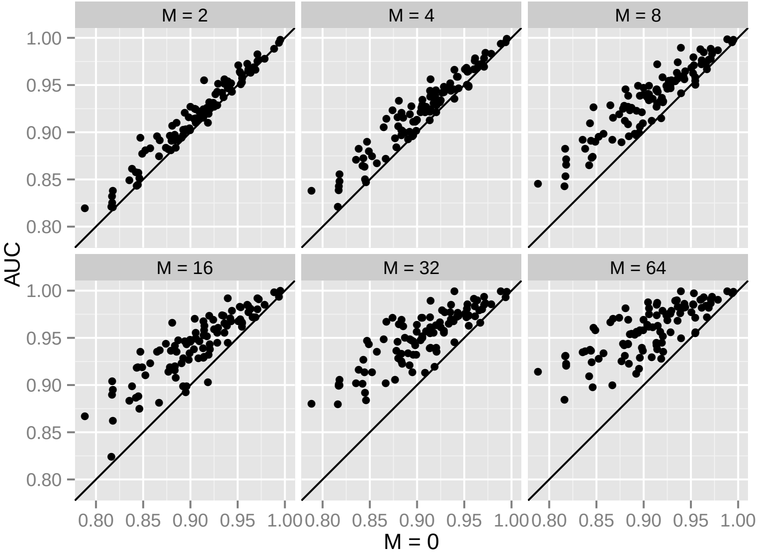
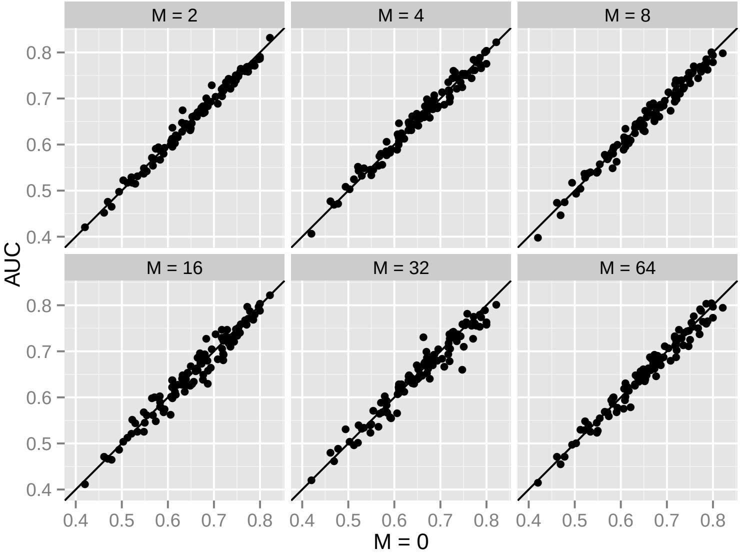
freq class '1'
heart
iono
magic
mammo
monks3
musk1
musk2
ozone1
ozone8
spam

Stochastic fraction effect (best)



Stochastic fraction effect (worst)



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Wisconsin data ($N = 547$)

- Launched
  2×18 servers $\times 32$ cores $= 1,152$ CPU core cluster on Amazon EC2
  $\Rightarrow$ 576 Dublin & 576 São Paulo
- Fit 50 trees in Dublin, 50 in São Paulo
  - unique `set.seed()` for each region
- Data split into 17 shards of 32 obs $+ 1$ shard 3 obs $\Rightarrow$ 1 datum per core!
- Reduction sum of votes in each region and combine regions $\Rightarrow$ 100 tree forest

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amazon web services

1h 36m

US$ 23.86

Other / Future Work

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1. Semi-parametric naive Bayes with logistic decision boundary
   - embedded approximation to logistic regression
2. Linear models
   - gradient decent based method
   - ridge penalties
   - lasso(?)
3. Multi-party evaluation of system reliability
   - keep system design secret
   - keep component lifetime test data secret
4. Approximate Bayesian Computation
   - classifier replacing summary statistics

References I

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