

C++ DP-GBDT Side-channel Analysis

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1 Secrecy

1.1 Dataset and parameters

entity	secret	parameter	secret
content of X	✓	nb_trees	×
X_cols_size	×	learning_rate	×
X_rows_size	×	privacy_budget	×
content of y	✓	task	×
y_rows_size	×	max_depth	×
		min_samples_split	×
		balance_partition	×
		gradient_filtering	×
		leaf_clipping	×
		scale_y	×
		use_decay	×
		l2_threshold	×
		l2_lambda	×
		cat_idx	×
		num_idx	×
		inferred from those	secret
		nb_samples per tree	×

While building a single tree

entity	secret	
X_subset	✓	
X_subset_cols_size	×	
X_subset_rows_size	✓	
y_subset	✓	
y_subset_rows_size	✓	
gradients	✓	
gradients_size	✓	

1.2 DP imperfections of the algorithm

- **init_score**, (=mean in regression, =most common feature in classification) leaks information about which feature values are in the dataset. Would need to add noise.
- **compute_gain** is done on the real data points. This was not addressed by the DPBoost paper. Would also need to add noise there.
- GDF is also problematic. changing one data point could have an impact on 2 trees.

2 main

No data dependent operations are done, therefore no side channel leakage. Securely getting the model parameters and dataset into and the resulting model out of the enclave is not among the challenges of this thesis.

Pseudocode 1: main

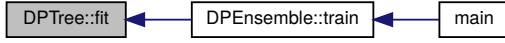
```
1 function main()
  // get parameters and dataset
2  parameters = get_params()
3  dataset = get_dataset()
  // create 5 train/test splits for cross validation
4  cv_splits = create_cross_val_inputs(dataset, 5)
  // do cross validation
5  for split in cv_splits do
6    ensemble = DPEnsemble(parameters)
7    ensemble.train(split.train)
    // predict using the test set
8    y_pred = ensemble.predict(split.test.X)
    // compute score
9    score = compute_score(split.test.y, y_pred)
```

3 class DPTree

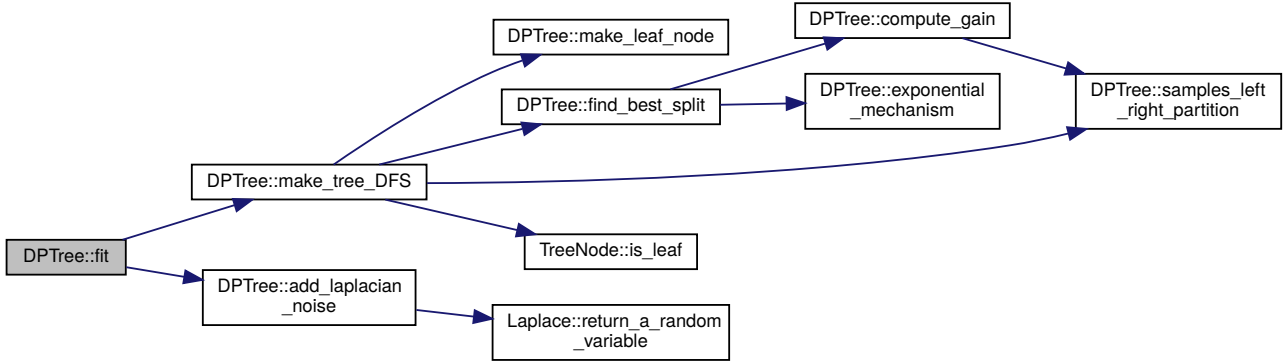
3.1 Methods

3.1.1 fit

Caller graph



Call graph



Variables

- must not leak:

dataset, leaves

- can leak:

params.*

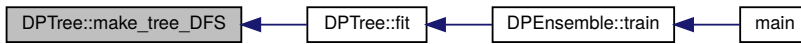
Pseudocode 2: DPTree::fit

```

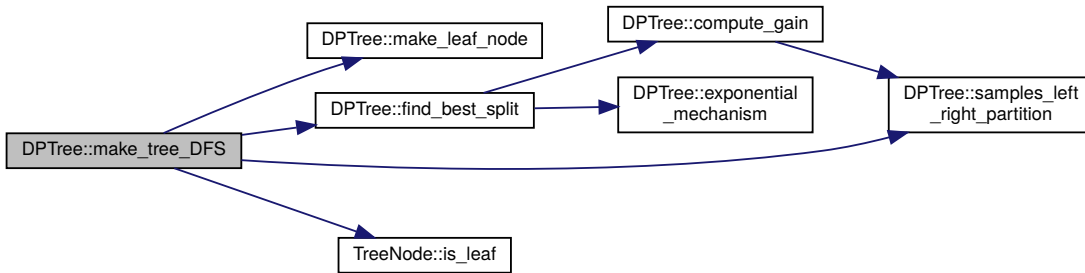
1 function fit()
  // all samples are live at the start
2  live_samples = [1,2,3,...,dataset.length]
  // build tree
3  this->root_node = make_tree_dfs(live_samples, 0)
  // leaf_clipping
4  if params.leaf_clipping or !params.gradient_filtering then ▷ params
5    threshold = params.l2 * (1 - η)tree_index
6    for leaf in this->leaves do ▷ number of leaves, which nodes are leaves
7    | leaf.prediction = clamp(leaf.prediction, -threshold, threshold)
  // add laplace noise to leaf values
8  privacy_budget_for_leaf_nodes =  $\frac{\text{tree\_privacy\_budget}}{2}$ 
9  laplace_scale =  $\frac{\text{params}.\Delta v}{\text{privacy\_budget\_for\_leaf\_nodes}}$ 
10 | add_laplacian_noise(laplace_scale)
  
```

3.1.2 make_tree_dfs

Caller graph



Call graph



Arguments / variables

- must not leak:

dataset, X_transposed, live_samples, gradients

- can leak:

params.min_samples_split, params.max_depth, curr_depth

Pseudocode 3: DPTree::make_tree_dfs

```

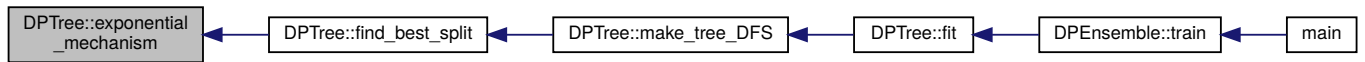
1 function make_tree_dfs(live_samples, curr_depth) ▷ size of live_samples
2   // max depth reached or not enough samples -> leaf node
3   if curr_depth == params.max_depth or len(live_samples) < params.min_samples_split then
4     |   TreeNode *leaf = make_leaf_node(curr_depth, live_samples) ▷ both branch conditions
5     |   return leaf
6   // find best split
7   TreeNode *node = find_best_split(X, gradients, live_samples, curr_depth)
8   // no split found
9   if node.is_leaf then ▷ number of leaves
10    |   return node
11  // prepare the new live samples to continue recursion
12  lhs, rhs = samples_left_right_partition(X, node.feature_index, node.feature_value) ▷ sizes
13  for sample in live_samples do ▷ size of live_samples
14    |   if lhs.contains(sample) then ▷ which samples go left/right
15    |   |   lhs_live_samples.insert(sample)
16    |   else
17    |   |   rhs_live_samples.insert(sample)
18  // recurse
19  node->left = make_tree_dfs(lhs_live_samples, curr_depth+1)
20  node->right = make_tree_dfs(rhs_live_samples, curr_depth+1)
21  return node
  
```

Recursion leakage

- number of splits in the tree
- number of splits/leaves observable by watching memory allocations

3.1.3 exponential_mechanism

Caller graph



Arguments / variables

- must not leak:

candidates

- can leak:

-

Pseudocode 4: DPTree::exponential_mechanism

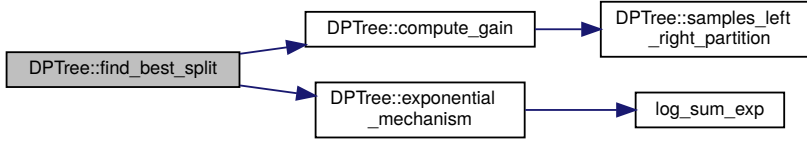
```
1 function exponential_mechanism(candidates) ▷ number of candidates
2   // if no split with positive gain, return, node will become a leaf
3   if cand.gain <= 0 forall cand in candidates then ▷ no good split exists, leaf creation
4     return -1
5   // calculate probabilities from the gains
6   for candidate in candidates do ▷ number of candidates
7     gains.append(candidate.gain)
8     if candidate.gain <= 0 then ▷ number of candidates with viable splits
9       probabilities.append(0)
10    else
11      lse =  $\log \sum_i \exp(\text{gains}_i)$ 
12      probabilities.append( $\exp(\text{candidate.gain} - \text{lse})$ )
13  // create a cumulative distribution from the probabilities, its values add up to 1
14  partials = std::partial_sum(probabilities)
15  // choose random value in [0,1]
16  rand_val = std::rand()
17  // return the corresponding split
18  for i = 0 to i = partials.size() - 1 do
19    if partials[i] >= rand_val then
20      return i
21  return -1
```

3.1.4 find_best_split

Caller graph



Call graph



Arguments / variables

- must not leak:

X, gradients, live_samples

- can leak:

params.*, tree_budget, curr_depth

Pseudocode 5: DPTree::find_best_split

```

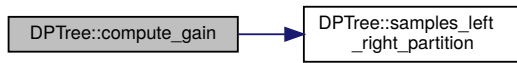
1 function find_best_split(X, gradients, live_samples, curr_depth) ▷ size of X, gradients
2   // determine node privacy budget
3   if params.use_decay then ▷ params.use_decay
4     if curr_depth == 0 then ▷ curr_depth == 0
5       | node_budget =  $\frac{\text{tree\_budget}}{2 * (2^{\text{max\_depth}+1} + 2^{\text{curr\_depth}+1})}$ 
6     else
7       | node_budget =  $\frac{\text{tree\_budget}}{2 * 2^{\text{curr\_depth}+1}}$ 
8   else
9     | node_budget =  $\frac{\text{tree\_budget}}{2 * \text{max\_depth}}$ 
10  // iterate over all possible splits
11  for feature_index in features do ▷ number of cols in X
12    for feature_value in X[feature_index] do ▷ number of rows in X
13      if "already encountered feature_value" then ▷ number of unique feature values
14        | continue
15      gain = compute_gain(X, gradients, live_samples, feature_index, feature_value)
16      if gain < 0 then ▷ number of splits with no gain
17        | continue
18      gain =  $\frac{\text{node\_budget} * \text{gain}}{2 * \Delta g}$ 
19      candidates.insert(Candidate(feature_index, feature_value, gain)) ▷ number of candidates
20  // choose a split using the exponential mechanism
21  index = exponential_mechanism(candidates)
22  // construct the node
23  TreeNode *node = new TreeNode(candidates[index]) ▷ internal node vs. leaf
24  return node
  
```

3.1.5 compute_gain

Caller graph



Call graph



Arguments / variables

- must not leak:

X, gradients, live_samples

- can leak:

params.l2_lambda, feature_index, feature_value

Pseudocode 6: DPTree::compute_gain

```
1 function compute_gain(X, gradients, live_samples, feature_index, feature_value) ▷ X, gradients
  // partition into lhs/rhs
2 lhs, rhs = samples_l_r_partition(X, live_samples, feature_index, feature_value) ▷ lhs/rhs size
3 lhs_size = lhs.size()
4 rhs_size = rhs.size()
  // return on useless split
5 if lhs_size == 0 or rhs_size == 0 then ▷ useless split
6   return -1
  // sums of lhs/rhs gains
7 lhs_gain = sum(gradients[lhs]) ▷ memory access pattern of left/right gradients
  rhs_gain = sum(gradients[rhs])
8 lhs_gain =  $\frac{\text{lhs\_gain}^2}{\text{lhs\_size} + \text{params.l2\_lambda}}$ 
9 rhs_gain =  $\frac{\text{rhs\_gain}^2}{\text{rhs\_size} + \text{params.l2\_lambda}}$ 
10 total_gain = max(lhs_gain + rhs_gain, 0) ▷ max might leak whether total_gain < 0
11 return total_gain
```

3.1.6 make_leaf_node

3.1.7 samples_left_right_partition

3.1.8 predict

4 class DPEnsemble

4.1 Methods

4.1.1 train

Caller graph

TODO

Call graph

TODO

Variables

- must not leak:

TODO

- can leak:

params.*, tree_params.*

Pseudocode 7: DPEnsemble::train

```
1 function train(dataset)
  // compute initial prediction
2  init_score = compute_init_score(dataset.y)
  // each tree gets the full budget since they train on distinct data
3  tree_privacy_budget = params.privacy_budget
  // train all trees
4  for tree_index = 0 to tree_index = nb_trees - 1 do
  // init/update gradients
5  update_gradients(dataset.gradients, tree_index)
  // sensitivity for internal nodes
6  tree_params. $\Delta g = 3 * (\text{params.l2\_threshold})^2$ 
  // sensitivity for leaf nodes
7  if params.gradient_filtering or !params.leaf_clipping then
8  | tree_params. $\Delta v = \frac{\text{params.l2\_threshold}}{1 + \text{params.l2\_lambda}}$ 
9  else
10 | tree_params. $\Delta v = \min(\frac{\text{params.l2\_threshold}}{1 + \text{params.l2\_lambda}}, 2 * \text{params.l2\_threshold} * (1 - \eta)^{\text{tree\_index}})$ 
  // determine number of rows
11 if params.balance_partition then
12 | number_of_rows =  $\frac{|D|}{\text{nb\_trees} - \text{tree\_index}}$ 
13 else
14 | number_of_rows =  $\frac{|D|\eta(1-\eta)^{\text{tree\_index}}}{1 - (1-\eta)^{\text{nb\_trees}}}$ 
```

4.1.2 predict

4.1.3 update_gradients

4.1.4 add_laplacian_noise

4.1.5 remove_rows

4.1.6 get_subset

5 other classes