

# C++ DP-GBDT Side-channel Analysis

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# 1 Severity List

## General

entity	secrecy
X	✓
X_cols_size	×
X_rows_size	×
y	✓
y_rows_size	×

parameter	secret
nb_trees	×
learning_rate	×
privacy_budget	×
task	×
max_depth	×
min_samples_split	×
balance_partition	×
gradient_filtering	×
leaf_clipping	×
scale_y	×
use_decay	×
l2_threshold	×
l2_lambda	×
cat_idx	×
num_idx	×

## While building a single tree

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

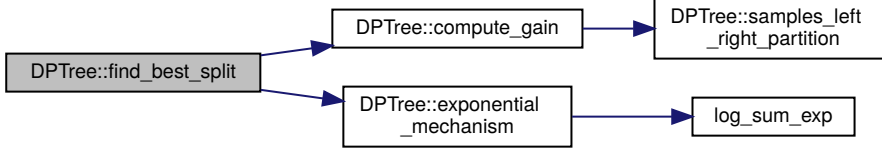
## 2 Building a single tree

### 2.1 find\_best\_split

Caller graph



Call graph



Arguments / used variables

variable	secret
X	✓
gradients	✓
curr_depth	?
tree_budget	×

params.use_decay	×
params. $\Delta g$	×
params.max_depth	×

---

**Algorithm 1:** find\_best\_split

---

```

1 Function find_best_split(X, gradients, curr_depth)
  // determine node privacy budget
  if params.use_decay then
3    if curr_depth == 0 then
4      node_budget =  $\frac{\text{tree\_budget}}{2^{*(2^{\text{max\_depth}}+1+2^{\text{curr\_depth}}+1)}}$ 
5    else
6      node_budget =  $\frac{\text{tree\_budget}}{2^{*2^{\text{curr\_depth}}+1}}$ 
7  else
8    node_budget =  $\frac{\text{tree\_budget}}{2^{*\text{max\_depth}}}$ 
  // iterate over all possible splits
9  for feature_index : features do
10    for feature_value : X[feature_index] do
11      if "already encountered feature_value" then
12        continue
13      gain = compute_gain(X, gradients, feature_index, feature_value)
14      if gain < 0 then
15        continue
16      gain =  $\frac{\text{node\_budget} * \text{gain}}{2 * \Delta g}$ 
17      candidates.insert(Candidate(feature_index, feature_value, gain))
  // choose a split using the exponential mechanism
18  index = exponential_mechanism(candidates)
  // construct the node
19  TreeNode *node = new TreeNode(candidates[index])
20  return node
  
```

---

#### 2.1.1 Side channel leakage

leakage in compute\_gain and exponential\_mechanism

From branches/loops

- params.use\_decay
- curr\_depth == 0
- number of features (columns of X)
- number of rows in X resp. length of gradients

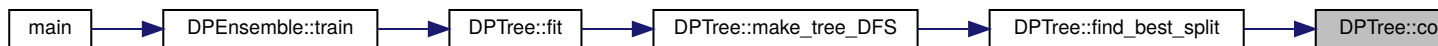
- number of unique feature values of a feature
- number of splits that don't give any gain
- number of split candidates

Potential arithmetic leakage ?

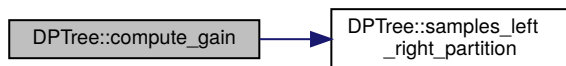
- Not sure about this in SGX though
- edge cases of variables appearing in formulas → tree\_budget and curr\_depth and  $\Delta g$  and gain

## 2.2 compute\_gain

### Caller graph



### Call graph



### Arguments / used variables

variable	secret	
X	✓	
gradients	✓	
feature_index	×	
feature_value	×	
params.l2_lambda	×	

---

### Algorithm 2: compute\_gain

---

```

1 Function compute_gain(X, gradients, feature_index, feature_value)
  // // partition into lhs/rhs
2  lhs, rhs = samples_left_right_partition(X, feature_index, feature_value)
3  lhs_size = lhs.size()
4  rhs_size = rhs.size()
  // return on useless split
5  if lhs_size == 0 || rhs_size == 0 then
6    return -1
  // sums of lhs/rhs gains
7  lhs_gain = sum(gradients[lhs])
8  rhs_gain = sum(gradients[rhs])
9  lhs_gain =  $\frac{\text{lhs\_gain}^2}{\text{lhs\_size} + \text{params.l2\_lambda}}$ 
10 rhs_gain =  $\frac{\text{rhs\_gain}^2}{\text{rhs\_size} + \text{params.l2\_lambda}}$ 
11 total_gain = lhs_gain + rhs_gain
12 total_gain = max(total_gain, 0)
13 return total_gain
  
```

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### 2.2.1 Side channel leakage

leakage in samples\_left\_right\_partition

From branches/loops/function calls

- size (#rows) of X/gradients
- lhs/rhs size
- whether it's a useless split

- memory access pattern of left/right gradients
- max function might leak whether total\_gain < 0

Potential arithmetic leakage ?

- edge cases of variables appearing in formulas → lhs\_gain and lhs\_size, rhs respectively.