THE MINIMAL AND MAXIMAL SENSITIVITY OF THE
SIMPLIFIED WEIGHTED SUM FUNCTION

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ABSTRACT. Sensitivity is an important complexity measure of Boolean functions. In this paper we present properties of the minimal and maximal sensitivity of the simplified weighted sum function. A simple close formula of the minimal sensitivity of the simplified weighted sum function is obtained. A phenomenon is exhibited that the minimal sensitivity of the weighted sum function is indeed an indicator of large primes, that is, for large prime number \( p \), the minimal sensitivity of the weighted sum function is always equal to one.

1. Introduction

It is well-known that Boolean functions are of most importance in the design of circuits and chips for almost all various electronic instruments. Indeed, as the digital computer system relies on the binary algebraic operations, the theory of Boolean functions are playing a more and more significant role in most areas of current and future technology, as well as in both natural science and social science, cf. (Crama and Hammer, 2001) for details. As a specific example, Boolean functions play a key role in cryptography for creating symmetric key algorithms, which is well-known closely related to number theory. The sensitivity concept of Boolean functions is originally introduced in (Cook et al., 1986). In practice, sensitivity is used as a combinatorial complexity measure of various Boolean models (Sauerhoff, 2003) (Sauerhoff and Sieling, 2005) (Canright et al., 2011) (Hatami et al., 2011).

Shparlinski (2007) showed a lower bound of the average sensitivity of the weighted sum Boolean function, also known as laced Boolean function. And he developed a conjecture about the average sensitivity. Canright et al. (2011) gave a series of formulas of the average sensitivity of the weighted sum function. Recently, Li (2012) solved the Shparlinski’s conjecture by the bound on the average sensitivity of the weighted sum function. However, most existing researches focus on the average sensitivity of the weighted sum function. It is worth noting that the maximal and minimal sensitivities are also effective complexity measures of Boolean functions. This paper deals with the minimal sensitivity of the weighted sum Boolean function, which was originated from Savicky and Zak (2000) in their research of read-once branching programs and then had positions for a variety of complexity theory applications, cf. (Sauerhoff, 2003) (Sauerhoff and Sieling, 2005). Among other things, in our first main result Lemma 4.3 we obtain an amazingly simple close formula of the minimal sensitivity of the weighted sum function. In our second main result Theorem 4.4, a surprising phenomenon is found that the minimal sensitivity of the weighted sum function is indeed an indicator of large primes. That is, for prime...
number \( p \geq 5 \), the minimal sensitivity of the weighted sum function is always equal to one.

The remainder of this paper is organized as follows. In Section 2 we discuss the sensitivity of Boolean functions, especially the minimal sensitivity. Section 3 describes a new simplified weighted sum function. The main results are presented in Section 4. Finally, Section 5 concludes this paper with several open questions.

2. Sensitivity of Boolean functions

In this section we introduce the sensitivity of Boolean functions. For a Boolean function \( f(X) \) on \( n \) variables and an input

\[
X = (x_0, x_1, \ldots, x_n - 1) \in \mathbb{Z}_2^n
\]  

(2.1)

where \( n \)-dimensional space \( \mathbb{Z}_m^n = \{0, 1, \ldots, m - 1\}^n \), the sensitivity \( Sen(f, X) \) denotes the number of coordinates in \( X \) such that flipping one Boolean variable of \( X \) will change the function value of \( f(X) \). Explicitly, \( Sen(f, X) \) can be given by

\[
Sen(f, X) = \sum_{i=0}^{n-1} |f(X) - f(X \oplus e_i)|
\]  

(2.2)

where \( X \oplus e_i \) denotes a new vector with original Boolean variable values of \( X \) and \( x_i \) is flipped in the new vector.

The average sensitivity \( AS(f) \) denotes the expected value of \( Sen(f, X) \) on every possible input \( X \) over \( \mathbb{Z}_2^n \). Explicitly,

\[
AS(f) = 2^{-n} \sum_{X \in \mathbb{Z}_2^n} \sum_{i=0}^{n-1} |f(X) - f(X \oplus e_i)|.
\]  

(2.3)

Similarly, for every possible input \( X \) over \( \mathbb{Z}_2^n \), let \( maxS(f) \) and \( minS(f) \) be the maximal and minimal values of the sensitivity \( Sen(f, X) \), respectively.

2.1. Example of the Minimal Sensitivity in Practice. Much work (Sauerhoff and Sieling, 2005) (Shparlinski, 2007) is proposed to apply the average sensitivity of Boolean functions to practice, ranging from circuit complexity and the size of a decision tree. In this section, we offer an example of using the minimal sensitivity in practice.

Model checking (Clarke and Emerson, 1981) (Clarke et al., 1986) is a verification technique to search state transitions of systems, including hardware and software designs. During model checking, properties, such as assurance of system invariants and absence of error states, can be verified. However, exponential space of system states can easily exceed memory limit of computers. To alleviate this problem, bounded model checking (Biere et al., 1999) reduces model checking to a Boolean satisfiability problem by exploring only a subset of the real space state transitions.

To illustrate this reduction, we define \( S \) as a finite state system over a finite set of Boolean variables \( X \). Let \( S_i \) be a state of \( X \). \( S_0 \) denotes the initial state of \( X \). Define the predicate

\[
Init(S_i) = \begin{cases} 
1, & S_i = S_0; \\
0, & \text{otherwise.}
\end{cases}
\]  

(2.4)

Let the predicate \( Trans(S_i, S_{i+1}) \) denote the transition from state \( S_i \) to next state \( S_{i+1} \). Define the predicate
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\[
\text{Target}(S_i) = \begin{cases} 
1, & \text{if } S_i \text{ is a final state (e.g. an error state making systems incorrect)}; \\
0, & \text{otherwise.} 
\end{cases} 
\] (2.5)

By the above definitions we have the propositional formula

\[
\Phi_k = \text{Init}(S_i) \land \bigwedge_{i=0,...,k-1} (\text{Trans}(S_i, S_{i+1})) \land \bigvee_{i=0,...,k} (\text{Target}(S_i)) 
\] (2.6)

where \( k \) denotes the completeness threshold. The system is incorrect within \( k \) transitions if and only if the propositional formula \( \Phi_k \) is satisfiable within \( k \) steps.

Assume \( \text{Trans}(S_i, S_{i+1}) \) only changes the value of one Boolean variable at a time, the satisfiability problem can be simplified further by analyzing the sensitivity of \( \text{Target}(S_i) \). Since conventional binary code can be converted into the Gray code (Doran, 2007) and conversion of Gray to binary is also feasible, this assumption is valid in most cases. In these cases, \( \max S(\text{Target}) \) and \( \min S(\text{Target}) \) are as crucial as \( \text{AS}(\text{Target}) \) to predict the complexity of \( \text{Target}(S_i) \). Although \( \text{AS}(\text{Target}) \) gives us an overview of whether \( \Phi_k \) is easy to satisfy, \( \text{AS}(\text{Target}) \) cannot help algorithms to find a solution of the satisfiability problem in the shortest path. Comparatively, \( \max S(\text{Target}) \) represents the states which are very likely to reach the final state at the next step. And \( \min S(\text{Target}) \) represents the states which are very unlikely to reach the final state at the next step. Hence, \( \max S(\text{Target}) \) and \( \min S(\text{Target}) \) provide two other useful measures for the satisfiability problem of \( \Phi_k \).

However, previous studies have not addressed properties of the maximal and minimal sensitivities of Boolean functions. On this basis, we focus on the minimal sensitivity of a new simplified weighted sum function.

3. Weighted Sum Function

Previously, the definition of the weighted sum function is proposed according to the weighted sum with a residue ring modulo a prime number. Explicitly, it can be shown in the following (Savicky and Zak, 2000).

Let \( n \in \mathbb{N}^* \) and \( p \) is a prime number, \( p \geq n \) where no prime number \( q \) meets \( n \leq q < p \). For an input set \( X = (x_1, x_2, \ldots, x_n) \in \mathbb{Z}_2^n \), construct a function \( s(X) \) by

\[
s(X) = \sum_{k=1}^{n} kx_k (\mod p), 1 \leq s(X) \leq p. \] (3.1)

Then define the weighted sum function

\[
f(X) = \begin{cases} 
\text{if } x_{s(X)}, & 1 \leq s(X) \leq n; \\
x_1, & \text{otherwise.} 
\end{cases} \] (3.2)

As the previous weighted sum function is relatively complex, we define a simplified weighted sum Boolean function \( f(X) \) as follows. Let \( n \) be a positive integer.
For \( X = (x_0, x_1, \ldots, x_{n-1}) \in \mathbb{Z}_n^2 \), we define \( s(X) \) by
\[
s(X) = \sum_{k=0}^{n-1} kx_k (\mod \ n). \tag{3.3}
\]
We then define that
\[
f(X) = x_{s(X)}. \tag{3.4}
\]
This simplified weighted sum function is more convenient to use and compute.

4. Our Results

In this section we present several properties of the newly simplified weighted sum function.

**Theorem 4.1.** \( \max S(f) = n \).

**Proof.** Due to the specificity of the weighted sum function, this theorem is trivial. Given Boolean function \( f(X) \) and its input set \( X \) with \( n \) Boolean variables, there always exists an input \( X_1 \) where \( x_i = 0, i \in \{0, \ldots, n-1\} \). In this case, \( s(X_1) = 0 \) and \( f(X_1) = x_0 = 0 \). For \( 0 \leq i < n \), \( f(X_1 \oplus e_i) = x_i \), which is just flipped from 0 to 1. Thus, flipping any variable in \( X_1 \) always exists an input \( X \). Consider a boolean variable input \( X_1 \) where \( s(X_1) = \min_S(f) = 0 \) and \( f(X_1) = 0 \). In this case, \( s(X_1) = 0 \) and \( f(X_1) = 0 \). Hence, the maximum of sensitivity of the weighted sum function is \( n \). \( \square \)

**Theorem 4.2.** Let \( p \geq 3 \) be any prime number. If \( p^2 \mid n \), then \( \min S(f) = 0 \).

**Proof.** Assume \( n = p^2 q \). Consider a boolean variable input \( X_1 \) where \( x_i = 1 \) if \( i \equiv p - 1 \) (mod \( p \)), \( 0 \leq i < n \) and \( x_i = 0 \), otherwise. Then \( s(X_1) \) can be given by
\[
(p - 1 + 2p - 1 + \cdots + p^2 q - 1) \mod p^2 q = \frac{(p^2 q^2 + pq - 2q)p}{2} \mod p^2 q. \tag{4.1}
\]
Since \( p^2 q^2 + pq \) is even, so is \( p^2 q^2 + pq - 2q \). So we have the conclusion that \( p \mid s(X_1) \) and \( f(X_1) = 0 \).

On the other hand, if \( n \mid s(X_1) \), then we have
\[
p^2 q(p^2 q^2 + pq - 2q)p \Rightarrow pq(p^2 q^2 + pq - 2q \Rightarrow pq - 2q
\]
which is impossible. Then \( p \mid s(X_1) \) and \( s(X_1) > 0 \).

Assume \( x_i \) is flipped.

If \( i = mp - 1, m > 0 \), then \( s(X_1 \oplus e_i) \neq s(X_1) \) and \( s(X_1 \oplus e_i) = s(X_1) - mp + 1 + tp^2 q, t = 0 \) or 1. Then we have \( s(X_1 \oplus e_i) \mod p = 1 \). Since \( x_j = 0, j \mod p \neq p - 1, 0 \leq j < n, f(X_1 \oplus e_i) = x_{s(X_1 \oplus e_i)} \neq 0 \).

If \( 0 \leq i \mod p \leq p - 2 \), then \( s(X_1 \oplus e_i) = s(X_1) + i - tp^2 q, t = 0 \) or 1. Since \( 0 \leq s(X_1 \oplus e_i) \mod p \leq p - 2 \) and \( x_j = 0, j \mod p \neq p - 1, 0 \leq j < n, j \neq i, f(X_1 \oplus e_i) = 1 \) if and only if \( s(X_1 \oplus e_i) = i \). In this case, \( s(X_1) - tp^2 q = 0 \).

Then, we have
\[
\frac{(p^2 q^2 + pq - 2q)p}{2} = mp^2 q, m \in \mathbb{Z}
\]
\[
p^2 q^2 + pq - 2q = 2mpq
\]
\[
p^2 q + p - 2 = 2mp
\]
\[
p(pq + 1 - 2m) = 2
\]
where \( p \) and \( (pq + 1 - 2m) \) are two integers. Since \( p \geq 3 \), Eq. (4.2) is impossible. Then we have \( f(X_1 \oplus e_i) = 0 \). Hence, \( Sen(f, X_1) = 0 \) and \( \min S(f) = 0 \). \( \square \)
Lemma 4.3. Let \( k \in \mathbb{N} \) and an input \( X_1 \) be \( (x_0, x_1, \ldots, x_{n-1}) \) where \( x_i = 1, i \in \{0, 1, \ldots, n - 1\} \). Then we have

\[
Sen(f, X_1) = \begin{cases} 
0, & n = 4k + 2; \\
1, & n = 2k + 1; \\
2, & n = 4k.
\end{cases}
\]

Proof. By the definition of \( X_1 \) we have \( f(X_1) = 1 \) and

\[
s(X_1) = \frac{n(n - 1)}{2} \mod n. \tag{4.3}
\]

If \( n = 4k + 2 \), \( s(X_1) = 8k^2 + 6k + 1 \mod 4k + 2 \). Since \( 8k^2 + 6k + 1 \) is odd and \( 4k + 2 \) is even, we have \( s(X_1) \neq 0 \). If \( x_i \) is flipped, then \( s(X_1 \oplus e_i) = 8k^2 + 6k + 1 + (4k + 2)t - i, t \in \mathbb{Z} \). \( f(X_1 \oplus e_i) = 0 \) happens if and only if \( s(X_1 \oplus e_i) = i \). In this case, we have

\[
i = 8k^2 + 6k + 1 + (4k + 2)t - i \\
2i = 8k^2 + 6k + 1 + (4k + 2)t
\]

where \( 8k^2 + 6k + 1 \) is odd and \( 4k + 2 \) is even. There does not exist an integer \( i \) in \( f(X_1 \oplus e_i) = 0 \). Hence, \( f(X_1 \oplus e_i) = 1 \) and \( Sen(f, X_1) = 0 = minS(f) \) if \( n = 4k + 2 \).

If \( n = 2k + 1 \), \( s(X_1) = k(2k + 1) \mod 2k + 1 \). Thus we have \( s(X_1) = 0 \). If \( x_i \) is flipped, then

\[
s(X_1 \oplus e_i) = \begin{cases} 
0, & i = 0; \\
n - i, & \text{otherwise.}
\end{cases} \tag{4.5}
\]

\( f(X_1 \oplus e_i) = 0 \) happens if and only if \( s(X_1 \oplus e_i) = i \). Since \( n \) is odd and \( 2i \) is even, \( n - i \neq i \). \( f(X_1 \oplus e_i) = 1 \) if and only if \( i = 0 \). Thus, we have \( Sen(f, X_1) = 1 \) if \( n = 2k + 1 \).

If \( n = 4k \), \( s(X_1) = 2k(4k - 1) \mod 4k \). Since

\[
\frac{2k(4k - 1)}{4k} = \frac{4k - 1}{2} = 2k - \frac{1}{2}, \tag{4.6}
\]

we have \( s(X_1) = 2k \). \( f(X_1 \oplus e_i) = 0 \) happens if and only if \( s(X_1 \oplus e_i) = i \). In this case, \( i = 2k - i \) or \( i = 2k - i + 4k \). Thus we have \( i = k \) or \( 3k \). Hence, \( Sen(f, X_1) = 2 \) if \( n = 4k \). \( \square \)

Theorem 4.4. Let \( n = p \) where \( p \) is a prime number and \( p > 4 \), then \( minS(f) = 1 \).

Proof. It is clear that \( Sen(f) = 1 \) at \( x_0 = 1 \) and \( x_i = 0, 0 < i < p \). Then we have \( minS(f) \leq 1 \). \( minS(f) = 1 \) implies that the equation \( Sen(f, X) = 0 \) has no solutions.

We prove by contradiction. Suppose \( Sen(f, X) = 0 \) has a solution \( X_1 \) and \( j = s(X_1) \). Then we have \( j \neq 0 \). Otherwise, \( x_0 \) can always flip to make \( Sen(f, X_1) \geq 1 \).

Let \( D \) be a subset in \( \{0, 1, \ldots, p - 1\} \) such that the vector \( X_1 \) is viewed as the indicator function of \( D \), and let \( \overline{D} = \mathbb{Z}_p - D \). If \( j \in D \), for each \( i \in D \) and each \( k \in \overline{D} \), we have \( j - i \mod p \in D \) and \( j + k \mod p \in D \). Similarly, if \( j \in \overline{D} \), for each \( i \in D \) and each \( k \in \overline{D} \), we have \( j - i \mod p \in \overline{D} \) and \( j + k \mod p \in \overline{D} \).
Table 1. The relationship between the variable number and the minimal sensitivity

| Variable Number | mins(f) |
|-----------------|---------|
| 1,4,5,7,8,11,13,17,19,23 | 1       |
| 2,3,6,9,10,12,14,15,16,18,20,21,22,24,25,26 | 0       |

Define $x \pm D = \{x \pm d, d \in D\}$. If $j \in D$, the above argument then gives that $j - D \subseteq D$, and thus $j - D = D$. Noting that $j = s(X_1) = \sum_{d \in D} d$, sum up all the elements of the both sets $j - D$ and $D$ we obtain $|D|j - j \equiv j \pmod p$ and thus $|D| = 2$ since $p$ is prime and $j \neq 0$. Then we have $|D| = p - 2$. For each $k \in D$, $j + k \pmod p$ runs over $p - 2$ different values. When $p > 4$, $j + k \pmod p \in D$ does not hold for each $k \in D$ due to $p - 2 > 2$. Thus we deduce $j \not\in D$.

Since $j \not\in D$, $j + D \subseteq D$. Thus $j + D = D$. Sum up all the elements of the both sets $j + D$ and $D$, we obtain $(p - |D|)j - j \equiv -j \pmod p$ and thus $|D| = p$ since $p$ is prime and $j \neq 0$. $|D| = p$ implies $j \in D$. This is a contradiction to $j \not\in D$.

By Lemma 4.3 we also derive that $\text{Sen}(f,X) = 0$ does not hold when $|D| = p$. Note that $p > 4$ is crucial in this theorem. If $p = 2$, $f(X) = 0$ only at $x_0 = 1, x_1 = 1$. If $p = 3$, $f(X) = 0$ only at $x_0 = 1, x_1 = 1, x_2 = 0$ and $x_0 = 1, x_1 = 0, x_2 = 1$. □

5. Conclusion and Open Questions

In this paper, we have explored the minimal sensitivity of a newly simplified weighted sum function. In terms of this function, we wrote a computer program which examined the relationship between the variable number and the minimal sensitivity for value $0 < n < 27$. The results are shown in Table 1. Other properties of the minimal sensitivity may be investigated. Related open questions are the following.

- It remains open whether $\text{minS}(f) = 0$ always holds when $n > 8$, $n$ is not a prime number.
- It is not clear whether other kinds of weighted sum functions have similar properties of the minimal sensitivity.

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