Complexity Results for Aggregating Judgments using Scoring or Distance-Based Procedures

Ronald de Haan, and Marija Slavkovik

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Complexity Results for Aggregating Judgments using Scoring or Distance-Based Procedures

Ronald de Haan
Technische Universität Wien
dehaan@ac.tuwien.ac.at

Marija Slavkovik
University of Bergen
Marija.Slavkovik@uib.no

ABSTRACT
Judgment aggregation is an abstract framework for studying collective decision making by aggregating individual opinions on logically related issues. Important types of judgment aggregation methods are those of scoring and distance-based methods, many of which can be seen as generalisations of voting rules. An important question to investigate for judgment aggregation methods is how hard it is to find a collective decision by applying these methods. In this article we study the complexity of this “winner determination” problem for some scoring and distance-based judgment aggregation procedures. Such procedures aggregate judgments by assigning values to judgment sets. Our work fills in some of the last gaps in the complexity landscape for winner determination in judgment aggregation. Our results reaffirm that aggregating judgments is computationally hard and strongly point towards the necessity of analyzing approximation methods or parameterized algorithms in judgment aggregation.

CCS Concepts
• Theory of computation → Problems, reductions and completeness; • Computing methodologies → Artificial intelligence;

Keywords
Judgment aggregation; computational complexity; winner determination; scoring procedures; distance-based procedures

1. INTRODUCTION
“Should we recommend buying the ticket now?”. “Should we wait, would the tickets sell out?”. “Does the customer want this ticket?”. These questions, or issues, cannot be independently answered as they are logically related. For instance, a yes-answer on the first question implies a yes-answer on either the second or the third question. Aggregating binary answers from multiple sources to questions such as these is the focus of judgment aggregation studies [18]. Judgment aggregation is a social choice discipline that generalises voting and preference aggregation [7, 27], and has been investigated using computer science methods in the field of computational social choice [12].

One of the topics studied in computational social choice is the computational complexity analysis of problems related to aggregation functions. One particular problem that is highly relevant is the problem of determining the outcomes of the aggregation procedure. In voting, the complexity of this problem indicates how difficult it is to find the winners of an election by using a particular voting method. Starting from the seminal work by Bartholdi, Tovey and Trick [2], numerous articles explore this topic and today the complexity landscape of the winner determination problem in voting is well covered. In judgment aggregation, the “winner” is a set of truth-value assignments, i.e., judgments, to a set of logically related issues. Namely, judgment aggregation functions aggregate a profile of judgments, which is a collection of individual judgment sets, into a collective judgment set. Judgment aggregation is a much younger discipline with fewer aggregation methods investigated in the literature, but even so the complexity of the “winner determination” problem is not studied for every known method in the literature.

The aim of this paper is to cover more of this gap.

The winner determination problem in judgment aggregation has been studied in various papers [14, 15, 28] covering the following judgment aggregation methods: Premise Based Procedure, Condorcet Admissible Set, Slater, Kemeny (also known as Median Rule), Young, Tideman, and MNAC1. Furthermore, Jamroga and Slavkovik [21] show some bounds for this problem for the class of distance-based judgment aggregation methods.

Contributions.
In this paper, we analyze the computational complexity of the winner determination problem for several judgment aggregation methods:
• the reversal scoring method introduced by Dietrich [6],
• the distance-based method for the Hamming distance and addition as aggregator function, introduced as the arbitration belief merging aggregator by Konieczny and Pino Pérez [23] and as judgment aggregator by Lang, Pigozzi, Slavkovik and Van der Torre [26], and
• the distance-based methods for the geodesic distance and addition as aggregator function, as introduced by Duddy and Piggins [9].

The first of these methods is a member of the class of scoring judgment aggregators and the second and third are from

1The reader can consult for example [26] for an integral overview of aggregation methods in judgment aggregation.
the class of distance-based aggregators. We show that deciding whether a judgment set can be selected as winner for a given profile by the first two of these methods is $\Theta^P_2$-complete (Theorems 2 and 3). For the third method, this problem is $\Theta^P_2$-complete (Theorem 4).

Both the scoring aggregators and the distance-based aggregators aggregate judgments by assigning values to show how similar a particular judgment set is to the aggregated profile. The distance-based aggregators are defined with respect to a distance that measures how different two judgment sets are. The scoring aggregators are defined with respect to a scoring function which attaches a value for each judgment in a judgment set. In this paper, we also show the general result that if the scoring function is computable in polynomial time, deciding whether a judgment set can be selected as winner for a given profile is in the class $\Theta^P_2$ (Theorem 1).

The completeness results that we establish for the winner determination problem, for various aggregators, are important steps for identifying what algorithmic approaches could work well to solve this problem in applied settings.

2. PRELIMINARIES

In this section, we begin by describing the formal framework that we use to model judgment aggregation scenarios (as used by, e.g., [8, 14, 28]), and briefly surveying some relevant notions from the theory of computational complexity.

Judgment Aggregation.

A propositional formula is doubly-negated if it is of the form $\neg\neg\varphi$. For every propositional formula $\varphi$, we let $\neg\varphi$ denote the complement of $\varphi$, i.e., $\neg\varphi = \neg\neg\varphi$ if $\varphi$ is not of the form $\neg\neg\varphi$, and $\neg\neg\varphi = \psi$ if $\varphi$ is of the form $\neg\neg\varphi$. For a propositional formula $\varphi$, the set $\text{Var}(\varphi)$ denotes the set of all variables occurring in $\varphi$.

An agenda is a finite, nonempty set $\Phi$ of formulas that does not contain any doubly-negated formulas and that is closed under complementation. Moreover, if $\Phi = \{\varphi_1, \ldots, \varphi_n\}$ is an agenda, then we let $[\Phi] = \{\varphi_1, \ldots, \varphi_n\}$ denote the pre-agenda associated to the agenda $\Phi$. We denote the bitsize of the agenda $\Phi$ by $\text{size}(\Phi) = \sum_{\varphi \in \Phi} |\varphi|$. A judgment set $J$ for an agenda $\Phi$ is a subset $J \subseteq \Phi$. A judgment set $J$ is complete if $\varphi \in J$ or $\neg\varphi \in J$ for all $\varphi \in \Phi$; and it is consistent if there exists an assignment that makes all formulas in $J$ true. Intuitively, the consistent and complete judgment sets are the opinions that individuals and the group can have.

We associate with each agenda $\Phi$ an integrity constraint $\Gamma$, that can be used to further restrict the set of feasible opinions. Such an integrity constraint consists of a single propositional formula. A judgment set $J$ is $\Gamma$-consistent if there exists a truth assignment that simultaneously makes all formulas in $J$ and $\Gamma$ true. Let $J(\Phi, \Gamma)$ denote the set of all complete and $\Gamma$-consistent subsets of $\Phi$. We say that finite sequences $J \in J(\Phi, \Gamma)$ of complete and $\Gamma$-consistent judgment sets are profiles, and where convenient we equate a profile $J = \langle J_1, \ldots, J_n \rangle$ with the (multiset) $\{J_1, \ldots, J_n\}$. A judgment aggregation procedure (or rule) for the agenda $\Phi$ and the integrity constraint $\Gamma$ is a function $F$ that takes as input a profile $J \in J(\Phi, \Gamma)$, and that produces a non-empty set of non-empty judgment sets. We call a judgment aggregation procedure $F$ resolute if for any profile $J$ it returns a singleton; otherwise, we call $F$ irresolute.

The Polynomial Hierarchy.

We begin with reviewing some basic notions from computational complexity. We assume the reader to be familiar with the complexity classes P and NP, and with basic notions such as polynomial-time reductions. For more details, we refer to textbooks on computational complexity theory (see, e.g., [1]). We would like to remind you of the quintessential NP-complete problem SAT.

- **Instance**: A propositional formula $\varphi$.
- **Question**: Is there an interpretation that satisfies $\varphi$?

We briefly review the classes of the Polynomial Hierarchy (PH) [29, 33, 36, 38]. In order to do so, we consider quantified Boolean formulas. A quantified Boolean formula (in prenex form) is a formula of the form $Q_1x_1Q_2x_2\ldots Q_nx_n \psi$, where all $x_i$ are propositional variables, each $Q_i$ is either an existential or a universal quantifier, and $\psi$ is a (quantifier-free) propositional formula over the variables $x_1, \ldots, x_n$.

Truth for such formulas is defined in the usual way.

To consider the complexity classes of the PH, we restrict the number of quantifier alternations occurring in quantified Boolean formulas, i.e., the number of times where $Q_i \neq Q_{i+1}$. We consider the complexity classes $\Sigma^P_k$ and $\Pi^P_k$ for each $k \geq 1$. Let $k \geq 1$ be an arbitrary, fixed constant. The complexity class $\Sigma^P_k$ consists of all decision problems for which there exists a polynomial-time reduction to the problem $\text{QSat}_k$, that is defined as follows. Instances of the problem $\text{QSat}_k$ are quantified Boolean formulas of the form $\exists x_1\exists x_2\ldots \exists x_k \varphi$, where $Q_k = \exists$ if $k$ is odd and $Q_k = \forall$ if $k$ is even, where $1 \leq \ell_1 \leq \cdots \leq \ell_k$, and where $\varphi$ is quantifier-free. The problem is to decide if the quantified Boolean formula is true. The complementary class $\Pi^P_k$ consists of all decision problems for which there exists a polynomial-time reduction to the problem $\text{co-QSat}_k$, that is complementary to the problem $\text{QSat}_k$. The Polynomial Hierarchy (PH) contains these classes $\Sigma^P_k$ and $\Pi^P_k$.

Alternatively, one can characterize the class $\Sigma^P_k$ using non-deterministic polynomial-time algorithms with access to an oracle for an NP-complete problem. Let $O$ be a decision problem. A Turing machine $M$ with access to an $O$ oracle is a Turing machine with a dedicated oracle tape and dedicated states $q_{query}$, $q_{yes}$, and $q_{no}$. Whenever $M$ is in the state $q_{query}$, it does not proceed according to the transition relation, but instead it transitions into the state $q_{yes}$ if $x \in O$, and into the state $q_{no}$ if $x \notin O$. Intuitively, the oracle solves arbitrary instances of $O$ in a single time step. The class $\Sigma^P_k$ consists of all decision problems that can be solved in polynomial time by a nondeterministic Turing machine that has access to an $O$ oracle, for some $O \in \text{NP}$.

We will also refer to the complexity class $\Theta^P_2$, that consists of all decision problems that can be solved by a polynomial-time algorithm that queries an NP oracle $O(\log n)$ times. The following two problems are complete for the class $\Theta^P_2$ under polynomial-time reductions. The first is the MAX-MAX. We refer to the complexity class $\Theta^P_2$, that consists of all decision problems that can be solved by a polynomial-time algorithm that queries an NP oracle $O(\log n)$ times. The following two problems are complete for the class $\Theta^P_2$ under polynomial-time reductions. The first is the MAX-MAX. We refer to the complexity class $\Theta^P_2$, that consists of all decision problems that can be solved by a polynomial-time algorithm that queries an NP oracle $O(\log n)$ times. The following two problems are complete for the class $\Theta^P_2$ under polynomial-time reductions. The first is the MAX-MAX.
The second is the problem MaxCardScepticalInference from [28], which was proved to be \( \Theta^p_2 \)-complete [31] (under the name Cardinality-Maximizing Base Revision). A supernormal default theory is a pair \( D = (\Delta, \beta) \) with \( \Delta = \{ \varphi_1, \ldots, \varphi_r \} \), where \( \varphi_1, \ldots, \varphi_r, \beta \) are propositional logic formulas. A propositional formula \( \alpha \) is a maxcard sceptical inference of \( D \) iff \( S \cup \{ \beta \} \models \alpha \) for every \( S \) that is a maximally consistent subset of \( \Delta \) with respect to set cardinality. The MaxCard Sceptical Inference takes an instance consisting of \( D, \beta \) and \( \alpha \) and returns yes if \( \alpha \) is a maxcard sceptical inference of \( D \).

MaxCardScepticalInference

**Instance:** A supernormal default theory \( D = (\Delta, \beta) \), propositional formula \( \alpha \).

**Question:** Is \( \alpha \) a maxcard sceptical inference of \( D \)?

In addition, we will refer to the complexity class \( \Theta^p_3 \), that consists of all decision problems that can be solved by a polynomial-time algorithm that queries an \( \Sigma^p_3 \) oracle \( O(\log n) \) times. The following problem is complete for the class \( \Theta^p_3 \) under polynomial-time reductions.

QSat2-Max-Model

**Instance:** A satisfiable instance \( \varphi \) of QSat2, where \( \varphi = \exists X \forall Y \psi \), and a variable \( w \in \text{Var}(\varphi) \).

**Question:** Is there a truth assignment \( \alpha : X \rightarrow \{0, 1\} \) s.t. \( \psi[\alpha] \) is valid, that sets a maximal number of variables in \( X \) to true (among all such assignments making \( \psi[\alpha] \) valid), and that sets \( w \) to true?

In the rest of the paper we are concerned with studying the computational complexity of the following problem defined for a judgment aggregator \( F \).

**OUTCOME(F)**

**Instance:** An agenda \( \Phi \) with an integrity constraint \( \Gamma \), a profile \( J \in \mathcal{J}(\Phi, \Gamma)^+ \) and subsets \( L, L_1, \ldots, L_n \subseteq \Phi \) with \( u \geq 0 \).

**Question:** Is there a judgment set \( J^* \in F(J) \) s.t. \( L \subseteq J^* \) and \( L_i \not\subseteq J^* \) for each \( i \in \{1, \ldots, u\} \).

In the next two sections we consider members of two classes of judgment aggregators: scoring methods and distance-based methods.

### 3. SCORING METHODS

A score \( s : \mathcal{J}(\Phi, \Gamma) \times \Phi \rightarrow \mathbb{R}^+ \) is a function that assigns a nonnegative value to a judgment in \( \Phi \) with respect to a rational judgment set from \( \mathcal{J}(\Phi, \Gamma) \). A scoring judgment aggregator \( F_s \) is a function defined for a score \( s \) as:

\[
F_s(J) = \arg\max_{J^* \in \mathcal{J}(\Phi, \Gamma)} \sum_{\varphi \in \Phi} s(J^*, \varphi).
\]  

Before we turn to the results that we develop in this section, we introduce some definitions and observations. An interpretation \( \omega \) for the agenda \( \Phi \) assigns a value true or false for each judgment in \( \Phi \). An interpretation satisfies a formula \( \varphi \in \Phi \) if it evaluates it to true while also evaluating \( \Gamma \) to true, in the classical propositional logic sense; we write \( \omega \models \varphi \). An interpretation satisfies a judgment set \( J \in \mathcal{J}(\Phi, \Gamma) \) iff \( \omega \models \bigwedge J \). The set \( \Omega \) is the set of all interpretations that satisfy \( \Phi \) with respect to \( \Gamma \).

#### Algorithm 1: OUTCOMEScore(J\(^*\), k)

1. Set \( k' := 0 \)
2. Set \( J := 0 \)
3. Guess an interpretation \( \omega \)
4. For each \( \langle \varphi, \sigma \rangle \in J^* \) do
   a. Set \( J := J \cup \{ \varphi \} \)
5. if \( \omega \models \Gamma \) then do
   a. Check \( \omega \models J \)
6. Check value(J\(^*\), J) \( \geq k \)

**Algorithm 2: OUTCOME(F\(_s\)) is in \( \Theta^p_2 \)**

1. Set \( m_s := 0 \)
2. Set \( m_s := \sum_{s(\varphi, \sigma) \in J^* \sigma} \)
3. Set \( k := \frac{m_s}{2} \)
4. while \( m_s \neq m_s \) do
5. if \( \text{OUTCOME}(J^*, k) \) then \( m_s := k \)
6. else \( m_s := k \)
7. \( k = \frac{m_s}{2} \)

Observe first that given a score \( s \), we can represent any profile \( J \) as a set of pairs \( J^* \) in the following way:

\[
J^* = \{ \langle \varphi, \sum_{i \in J^*} s(J^*, \varphi) \rangle \mid \varphi \in \Phi \} \tag{2}
\]

Let us define the value of a judgment set \( J \in F_s(J) \) with respect to a profile \( J \) and a score \( s \) as:

\[
\text{value}(J^*, J) = \sum_{\varphi \in J^*} \sigma. \tag{3}
\]

In this section, we will also consider the following auxiliary problem, defined for a score \( s \).

**OUTCOMEScore(J\(^*\), k)**

**Instance:** An agenda \( \Phi \), constraints \( \Gamma \), a profile \( J^* \in \Phi \times \mathbb{R}^+ \) and a real nonnegative number \( k \in \mathbb{R}^+ \).

**Question:** Is there a judgment set \( J^* \in \mathcal{J}(\Phi, \Gamma) \) s.t. value(J\(^*\), J\(^*\)) \( \geq k \)?

### 3.1 Scoring methods with polynomial scores

In this section, we show the general result that for any score \( s \) that is computable in polynomial time—that is, \( J^* \) can be computed from \( J \) in polynomial time—the winner determination problem OUTCOME(F\(_s\)) is in \( \Theta^p_2 \).

**Theorem 1.** If \( J^* \) can be computed from \( J \) in polynomial time, then \( \text{OUTCOME}(F_s) \) is in \( \Theta^p_2 \).

**Proof.** The proof is similar to the proof of Property 4.20 in [11]. We first consider the problem OUTCOMEScore(J\(^*\), k). Algorithm 1 shows that OUTCOME-Score(J\(^*\), k) is in NP.

We then show that OUTCOME(F\(_s\)) is in \( \Theta^p_2 \) via Algorithm 2. Algorithm 2 finds the maximal value \( k \) for which there is some judgment set \( J \) with value(J\(^*\), J\(^*\)) \( = k \). Then, checking whether there is such a judgment set s.t. \( L \subseteq J \) and \( L_i \not\subseteq J \) for all \( i \) can be done with one additional NP oracle query. \( \square \)
Matching $\Theta^p_2$-hardness results.

We showed that for any score $s$ for which $J^*$ can be computed from $J$ in polynomial time, the winner determination problem $\text{OUTCOME}(F_r)$ for the corresponding judgment aggregation procedure is contained in the class $\Theta^p_2$. This is an upper bound—the complexity of winner determination for such scoring procedures is not higher than $\Theta^p_2$.

Not every polynomial-time computable score $s$ leads to a judgment aggregation procedure that is also complete for the class $\Theta^p_2$ (taking some common complexity-theoretic assumptions into account). There are trivial counterexamples. For instance, the trivial score $s_0$ that always returns 0—that is, for which $s_0(J, \varphi) = 0$ for all $J$ and all $\varphi$—results in a judgment aggregation procedure $F_{s_0}$ for which the winner determination problem is in NP. Namely, all complete and $\Gamma$-consistent judgment sets $J$ get the same total score $\sum_{J_i \in J} s_0(J_i, \varphi) = 0$. Therefore, deciding whether there is a complete and $\Gamma$-consistent judgment set $J^*$ with maximum score and with $L \subseteq J^*$ and $L_i \not\subseteq J^*$ for all $i$ can be done nondeterministic polynomial time. In particular, this tells us that $\text{OUTCOME}(F_{s_0})$ is not $\Theta^p_2$-complete, unless the Polynomial Hierarchy collapses.

There are, however, natural scoring judgment aggregation procedures $F_s$ for which the score $s$ is computable in polynomial-time and for which the problem $\text{OUTCOME}(F_s)$ is $\Theta^p_2$-complete. One example of such a procedure is the simple scoring procedure [6], based on the score $s$ defined by letting $s(J, \varphi) = 1$ if $\varphi \in J$ and $s(J, \varphi) = 0$ if $\varphi \not\in J$. This procedure is also known as the Kemeny judgment aggregation procedure and its winner determination problem is known to be $\Theta^p_2$-complete [14, 15, 28].

3.2 Reversal scoring aggregator

In this section, we consider the reversal scoring procedure [6]. This procedure can be seen as a generalisation of the Borda rule in voting (for more details, we refer to Section 5). The reversal scoring procedure is defined as follows.

Let $J \in J(\Phi, \Gamma)$ be a complete and $\Gamma$-consistent judgment set for an agenda $\Phi$ and an integrity constraint $\Gamma$. Moreover, let $\varphi \in \Phi$. Then the reversal score $\text{rev}(J, \varphi)$ for $J$ is defined as the minimal number of formulas in $J$ that need to be negated to get a complete and $\Gamma$-consistent judgment set $J'$ that contains $\varphi$. Formally:

\[
\text{rev}(J, \varphi) = \min_{J' \in J(\Phi, \Gamma)} d_H(J', J).
\]

(Here $d_H$ denotes the Hamming distance between two complete judgment sets, i.e., $d_H(J, J') = |\{J_i \mid J_i' \neq J_i\}|$.)

Based on the reversal score, we get the reversal scoring judgment aggregation procedure $F_{\text{rev}}$, that is defined as follows:

\[
F_{\text{rev}}(J) = \arg\max_{J' \in J(\Phi, \Gamma)} \sum_{J_i \in J} \text{rev}(J_i, \varphi).
\]

The reversal scoring judgment aggregation procedure is irreversible, complete and $\Gamma$-consistent.

We show that the winner determination problem for the reversal scoring judgment aggregation procedure is $\Theta^p_2$-complete.

Since the reversal score is not computable in polynomial time (unless $P = \text{NP}$), we cannot directly apply Theorem 1. Nevertheless, $\text{OUTCOME}(F_{\text{rev}})$ is in $\Theta^p_2$.

**Lemma 1.** $\text{OUTCOME}(F_r)$ is in $\Theta^p_2$.

**Proof.** We show membership in $\Theta^p_2$ by describing a polynomial-time algorithm that solves $\text{OUTCOME}(F_r)$ by making a logarithmic number of queries to (different) NP oracles. Let $(\Phi, \Gamma, J, L_1, \ldots, L_u)$ specify an instance of $\text{OUTCOME}(F_r)$, where $J = (J_1, \ldots, J_u)$.

Firstly, we determine the following value:

\[
b_1 = \sum_{J_i \in J} \min_{J_i' \subseteq J_i, J_i' \neq J_i} d_H(J_i', J_i).
\]

We will determine $b_1$ by means of binary search using one NP oracle. After having determined the value $b_1$, we can use this value to determine the maximum reversal score $b_2$ for any complete and $\Gamma$-consistent judgment set $J' \in J(\Phi, \Gamma)$ by means of binary search using another NP oracle. This second oracle uses the value $b_1$. Finally, after having determined the value $b_2$, we can decide whether the instance is a yes-instance by using one last query to the second oracle.

The NP oracle $Q_1$ that we will use to determine $b_1$ decides—for a given natural number $b$—whether there exists a complete and $\Gamma$-consistent judgment set $J^* \in J(\Phi, \Gamma)$ for which the total Hamming distance from these judgment sets to the given sets $L'_1, L'_2, \ldots, L'_u$ is not $\Theta^p_2$-complete, unless the Polynomial Hierarchy collapses. This problem oracle solves is in NP.

We have a straightforward upper bound of $2^m$ for the value of $b_1$. Therefore, we can find the exact value of $b_1$ using $O(\log \log 2 + 2 \log n)$ queries to the oracle $Q_1$.

Next, we will determine the following value:

\[
b_2 = \max_{J' \in J(\Phi, \Gamma)} \sum_{J_i \in J} \min_{J_i' \subseteq J_i, J_i' \neq J_i} d_H(J_i', J_i).
\]

The NP oracle $Q_2$ that we will use for this decides—for given sets $L'_1, L'_2, \ldots, L'_u \subseteq \Phi$ and a given natural number $b$—whether there exists a complete and $\Gamma$-consistent judgment set $J^* \in J(\Phi, \Gamma)$ s.t. $L'_i \subseteq J^*$, $L'_i \not\subseteq J^*$ for each $L'_i$, and $\sum_{J_i \in J} \sum_{J_i' \subseteq J_i, J_i' \neq J_i} d_H(J_i, J_i') \geq b$. The problem $Q_2$ that this oracle solves is in NP. Because we know the value of $b_1$, we can guess for each $\varphi \in \Phi$ and each $J_i \in J$ a judgment set $J_i$ with $\varphi \in J_i$ and verify that the total Hamming distance from these judgment sets to the sets $J_i \in J$ is exactly $b_1$. This allows us to show that the problem $Q_2$ is in NP.

We can now determine the value of $b_2$ by using binary search. We have a straightforward upper bound of $2^m$ for $b_2$. Therefore, we can find the exact value of $b_2$ using $O(\log \log 2 + 2 \log n)$ queries to the oracle $Q_2$ (where we take $L' = \emptyset$ and where we use no sets $L'_i$, i.e., $u = 0$).

Finally, using one more query to the oracle $Q_2$, we can decide whether there exists a complete and $\Gamma$-consistent judgment set $J^* \in J(\Phi, \Gamma)$ s.t.: (1) $L_i \subseteq J^*$, (2) $L_i \not\subseteq J^*$ for each $L_i$, and (3) $\sum_{J_i \in J} \sum_{J_i' \subseteq J_i, J_i' \neq J_i} d_H(J_i', J_i) \geq b_2$. For this query, we use $b = b_2$, $L = L'_1$, and $L_i = L'_i$ for each $i$. The instance of $\text{OUTCOME}(F_r)$ is a yes-instance iff this last oracle query returns “yes.” This completes our description of the algorithm that witnesses membership in $\Theta^p_2$.

**Theorem 2.** $\text{OUTCOME}(F_r)$ is $\Theta^p_2$-hard.

**Proof.** Membership in $\Theta^p_2$-hardness by giving a reduction from the $\Theta^p_2$-complete problem $\text{MAX-MODEL}$ [5, 24, 37]. Let $(\varphi, w)$ be an
instance of MAX-MODEL, where $\varphi$ is a satisfiable propositional formula with $\text{Var}(\varphi) = \{x_1, \ldots, x_n\}$ and $w \in \text{Var}(\varphi)$. Without loss of generality, we may assume that the truth assignment that sets every variable $x_i$ to false satisfies $\varphi$. We construct an agent $\Phi$, an integrity constraint $\Gamma$, a profile $J$, and a set $L \subseteq \Phi$ s.t. there is some $J^* \in F_r(J)$ with $L \subseteq J^*$ iff there is a model of $\varphi$ that sets a maximum number of variables in $\text{Var}(\varphi)$ to true (among all models of $\varphi$) and that sets $w$ to true.

Let $m = 3n + 2$. We introduce new propositional variables $z_{\ell,j}$ for each $\ell \in [3]$ and each $j \in [m]$. We define $\Phi$ by letting $[\Phi] = \{x_1, \ldots, x_n\} \cup \{z_{\ell,j} : \ell \in [3], j \in [m]\}$. Moreover, we define $\Gamma$ as follows:

$$\Gamma = \bigwedge_{j_1, j_2 \in [m]} \left( \bigwedge_{\ell \in [3]} \neg z_{\ell,j_1} \rightarrow \varphi \right).$$

We let $L = \{w\}$. Finally, we define the profile $J = (J_1, J_2, J_3)$ as defined in Figure 1.

<table>
<thead>
<tr>
<th>$J$</th>
<th>$J_1$</th>
<th>$J_2$</th>
<th>$J_3$</th>
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<tbody>
<tr>
<td>$z_1$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$z_{2,1}$</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$z_{3,2}$</td>
<td>0</td>
<td>1</td>
<td>0</td>
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To illustrate the reversal scoring rule, but also the particular distance-based methods we consider in the next section, we use the so-called “doctrinal paradox” as an example. Consider the agenda $\Phi = \{p, \neg p, q, \neg q, r, \neg r\}$ and the integrity constraint $\Gamma = r \leftrightarrow (p \land q)$. We consider the profile $J$ given in Table 1. The set $m(J)$, constructing by adding those judgments from $\Phi$ that are supported by a majority of the agents in $J$, is inconsistent with $\Gamma$. The last two columns of the table list all the judgment sets that are selected by $F_r(J)$. For details of the intermediary calculations we refer to the literature [6, Table 3].

$$\begin{array}{ccccccc}
\text{J} & J_1 & J_2 & J_3 & m(J) & F_r(J) \\
\hline
p & 1 & 1 & 0 & 1 & 1 & 0 \\
q & 1 & 0 & 1 & 1 & 0 & 1 \\
r & 1 & 0 & 0 & 0 & 0 & 1 \\
\end{array}$$

Table 1: Profile for the doctrinal paradox example.

4. DISTANCE-BASED METHODS

A distance $d : \mathcal{J}(\Phi, \Gamma) \times \mathcal{J}(\Phi, \Gamma) \rightarrow \mathbb{R}^+$ is a function that satisfies identity of the indiscernible, symmetry and triangle inequality. A distance-based judgment aggregator $F_d^*$ is a function defined for a distance $d$ and an aggregation function $\ast$ as:

$$F_d^*(J) = \arg \min_{\gamma \in \mathcal{J}(\Phi, \Gamma)} \ast(d(J, J_1), \ldots, d(J, J_n)).$$

The aggregation function $\ast$ usually used is $\Sigma$ or $\max$. To ease the notation, we will use the subscript $H$ instead of $d_H$ to indicate that the aggregator is defined using the Hamming distance.

The aggregator $F_d^*_H$ is well studied in judgment aggregation; it appears in many places under different names: Prototype [30], median rule [32], maximum weighted agenda rule [25], simple scoring rule [6] and distance-based procedure [14], see also [26]. Variants of this rule have been defined by Konieczny and Pino-Pérez [22] and Pigozzi [34]. The $F_d^*_H$ aggregator generalises the Kemeny voting method is one of the first problems to be shown to be $\Theta_2^P$-complete [15, 14, 28].

In this section, we will also consider the following auxiliary problem, defined for a distance $d$ and an aggregation function $\ast$.

**OUTCOME** ($d, \ast$)

*Instance:* An agenda $\Phi$, an integrity constraint $\Gamma$, a profile $J = (J_1, \ldots, J_n)$, a real nonnegative number $k \in \mathbb{R}^+$, and subsets $L, L_1, \ldots, L_n \subseteq \Phi$ with $u \geq 0$.

*Question:* Is there a judgment set $J^* \in \mathcal{J}(\Phi, \Gamma)$ s.t. $L \subseteq J^*_L$, $J^*_L \not\subseteq J^*$ for all $i$, and $\ast(d(J^*, J_1), \ldots, d(J^*, J_n)) \leq k$?

4.1 The max+Hamming distance aggregator

We show $\Theta_2^P$-completeness for $\text{OUTCOME}(F_d^*_\text{max})$—the problem of computing outcomes for the judgment aggregation procedure based on the Hamming distance with maximization as aggregator function.

For the profile in Table 1 we obtain $F_d^*_\text{max}(J) = \{p, q, r, \{p, \neg q, \neg r\}, \{\neg p, q, \neg r\}\}$. Namely, all of the profile judgment sets are selected, because in this case, as in other instances of MAX-MODEL, where $\varphi$ is a satisfiable propositional formula with $\text{Var}(\varphi) = \{x_1, \ldots, x_n\}$ and $w \in \text{Var}(\varphi)$. Without loss of generality, we may assume that the truth assignment that sets every variable $x_i$ to false satisfies $\varphi$. We construct an agent $\Phi$, an integrity constraint $\Gamma$, a profile $J$, and a set $L \subseteq \Phi$ s.t. there is some $J^* \in F_r(J)$ with $L \subseteq J^*$ iff there is a model of $\varphi$ that sets a maximum number of variables in $\text{Var}(\varphi)$ to true (among all models of $\varphi$) and that sets $w$ to true.

Let $m = 3n + 2$. We introduce new propositional variables $z_{\ell,j}$ for each $\ell \in [3]$ and each $j \in [m]$. We define $\Phi$ by letting $[\Phi] = \{x_1, \ldots, x_n\} \cup \{z_{\ell,j} : \ell \in [3], j \in [m]\}$. Moreover, we define $\Gamma$ as follows:

$$\Gamma = \bigwedge_{j_1, j_2 \in [m]} \left( \bigwedge_{\ell \in [3]} \neg z_{\ell,j_1} \rightarrow \varphi \right).$$

We let $L = \{w\}$. Finally, we define the profile $J = (J_1, J_2, J_3)$ as defined in Figure 1.

<table>
<thead>
<tr>
<th>$J$</th>
<th>$J_1$</th>
<th>$J_2$</th>
<th>$J_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$z_1$</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$z_{2,1}$</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$z_{3,2}$</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

4. DISTANCE-BASED METHODS

A distance $d : \mathcal{J}(\Phi, \Gamma) \times \mathcal{J}(\Phi, \Gamma) \rightarrow \mathbb{R}^+$ is a function that satisfies identity of the indiscernible, symmetry and triangle inequality. A distance-based judgment aggregator $F_d^*$ is a function defined for a distance $d$ and an aggregation function $\ast$ as:

$$F_d^*(J) = \arg \min_{\gamma \in \mathcal{J}(\Phi, \Gamma)} \ast(d(J, J_1), \ldots, d(J, J_n)).$$

The aggregation function $\ast$ usually used is $\Sigma$ or $\max$. To ease the notation, we will use the subscript $H$ instead of $d_H$ to indicate that the aggregator is defined using the Hamming distance.

The aggregator $F_d^*_H$ is well studied in judgment aggregation; it appears in many places under different names: Prototype [30], median rule [32], maximum weighted agenda rule [25], simple scoring rule [6] and distance-based procedure [14], see also [26]. Variants of this rule have been defined by Konieczny and Pino-Pérez [22] and Pigozzi [34]. The $F_d^*_H$ aggregator generalises the Kemeny voting method is one of the first problems to be shown to be $\Theta_2^P$-complete [15, 14, 28].

In this section, we will also consider the following auxiliary problem, defined for a distance $d$ and an aggregation function $\ast$.

**OUTCOME** ($d, \ast$)

*Instance:* An agenda $\Phi$, an integrity constraint $\Gamma$, a profile $J = (J_1, \ldots, J_n)$, a real nonnegative number $k \in \mathbb{R}^+$, and subsets $L, L_1, \ldots, L_n \subseteq \Phi$ with $u \geq 0$.

*Question:* Is there a judgment set $J^* \in \mathcal{J}(\Phi, \Gamma)$ s.t. $L \subseteq J^*_L$, $J^*_L \not\subseteq J^*$ for all $i$, and $\ast(d(J^*, J_1), \ldots, d(J^*, J_n)) \leq k$?

4.1 The max+Hamming distance aggregator

We show $\Theta_2^P$-completeness for $\text{OUTCOME}(F_d^*_\text{max})$—the problem of computing outcomes for the judgment aggregation procedure based on the Hamming distance with maximization as aggregator function.

For the profile in Table 1 we obtain $F_d^*_\text{max}(J) = \{p, q, r, \{p, \neg q, \neg r\}, \{\neg p, q, \neg r\}\}$. Namely, all of the profile judgment sets are selected, because in this case, as in other
cases with small agendas and profiles with small number of agents, the $F^\max_{H}$ is not very selective.

**Theorem 3.** $\text{OUTCOME}(F^\max_{H})$ is $\Theta^P_3$-complete.

**Proof.** Let $J = (J_1, \ldots, J_p)$. To show that the problem $\text{OUTCOME}(F^\max_{H})$ is in $\Theta^P_3$ we can use Algorithm 2 with one minor adjustment—we set $m = |\Phi|/2$ in line 2, since the maximal Hamming distance that can have from another is $|\Phi|/2$ and thus, for any rational $J$ we have that $\text{max}(d(J_1), \ldots, d(J_p)) \leq |\Phi|/2$.

To show that $\text{OUTCOME}(F^\max_{H})$ is $\Theta^P_3$-hard, we make a reduction from MAXCARD SCEPTICAL INFERENCE to a judgment aggregation problem, as done in [28].

Consider $\Delta = \{\varphi_1, \ldots, \varphi_j\}$, $\beta$, and propositional formula $\alpha$. We construct an agenda $[\Phi_\Delta] = \{x_i, y_i, (x_i \land y_i) \rightarrow \varphi_i : i \in [1, \beta]\}$, $\varphi_i \in \Delta$, where $x_i, y_i$ are new propositional variables. We construct the profile $J_\Delta$ given in Table 2. Moreover, set $\gamma = \beta$, set $L = \{-\varphi \}$, and let $u = 0$.

Let $|\Delta| = n$. Consider a rational judgment set $J$ in $\mathcal{J}(\Phi, \beta)$ s.t. $((x_i \land y_i) \rightarrow \varphi_i) \not\in J$ for any $i \in [n]$. Let $D_m(J, J) = \text{max}(d(J_1), \ldots, d(J_p))$. Observe that if $J'$ is s.t. there exists a $i \in [n]$ for which $(x_i \land y_i) \rightarrow \varphi_i \not\in J'$, we have that $D_m(J', J) = 2p + D_m(J, J)$, thus such $J'$ will for sure not be in $F^\max_{H}(J_\Delta)$, therefore we do not consider them.

Let us define the sets $K_1, \ldots, K_4$, of cardinalities $k_1, k_2, k_3$ and $k_4$, respectively, as follows:

- $K_1 = \{(x_i, y_i, (x_i \land y_i) \rightarrow \varphi_i) \in J : i \in [n]\}$
- $K_2 = \{(x_i, \neg y_i, (x_i \land y_i) \rightarrow \varphi_i) \in J : i \in [n]\}$
- $K_3 = \{(\neg x_i, y_i, (x_i \land y_i) \rightarrow \varphi_i) \in J : i \in [n]\}$
- $K_4 = \{(\neg x_i, \neg y_i, (x_i \land y_i) \rightarrow \varphi_i) \in J : i \in [n]\}$

Observe that for any $J_i \in J$, $J_i \cap K_1$ is a singleton, $J_i \cap K_3$ is the empty set, for $j$ odd $J_i \cap K_2$ is the empty set and for even $J_i \cap K_2$ is the empty set. Given a judgment set $J_i \in J$, let $k$ be the index of the unique positive triple in $J_i$, namely $\{x_{k}, y_{k}, (x_{k} \land y_{k}) \rightarrow \varphi_{k}\} \subset J_i$. Let us define the number $k_d(J_i, J)$ as:

- $k_d(J_i, J) = 0$ if $\{x_{k}, y_{k}, (x_{k} \land y_{k}) \rightarrow \varphi_{k}\} \subset J_i$
- $k_d(J_i, J) = 1$ if $\{\neg x_{k}, y_{k}, (x_{k} \land y_{k}) \rightarrow \varphi_{k}\} \subset J_i$ or $\{x_{k}, \neg y_{k}, (x_{k} \land y_{k}) \rightarrow \varphi_{k}\} \subset J_i$.
- $k_d(J_i, J) = 2$ if $\{\neg x_{k}, \neg y_{k}, (x_{k} \land y_{k}) \rightarrow \varphi_{k}\} \subset J_i$.

The cells in Table 3 gives the possible distances between $J$ and a judgment set $J_i \in J$ for all cases.

Observe now that judgment sets $J_i \in J(\Phi, \beta)$ for which there exists a $J_i \in J$ s.t. $k_d(J_i, J) = 2$ cannot be included in $F^\max_{H}(J_\Delta)$. But since each $J_i \in J$ has exactly one positive triple, then if $k_d \neq 0$, there necessarily will exist at least

<table>
<thead>
<tr>
<th>$J_1$</th>
<th>$J_2$</th>
<th>$J_3$</th>
<th>$J_4$</th>
<th>$J_{p-1}$</th>
<th>$J_{2p}$</th>
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</thead>
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<tr>
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<td>$1$</td>
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</tr>
<tr>
<td>$(x_1 \land y_1) \rightarrow \varphi_1$</td>
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<td>$1$</td>
<td>$1$</td>
<td>$0$</td>
</tr>
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<td>$x_2$</td>
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<td>$1$</td>
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</tr>
<tr>
<td>$y_2$</td>
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<td>$1$</td>
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</tr>
<tr>
<td>$(x_2 \land y_2) \rightarrow \varphi_2$</td>
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<td>$1$</td>
<td>$0$</td>
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<td>$y_p$</td>
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</tr>
<tr>
<td>$(x_p \land y_p) \rightarrow \varphi_p$</td>
<td>$1$</td>
<td>$0$</td>
<td>$1$</td>
<td>$1$</td>
<td>$0$</td>
</tr>
</tbody>
</table>

**Table 2:** The profile $J$ used in the proof of Theorem 3.

<table>
<thead>
<tr>
<th>$j$ odd</th>
<th>$j$ even</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_d(J_i, J) = 0$</td>
<td>$k_d(J_i, J) = 1$</td>
</tr>
<tr>
<td>$k_d(J_i, J) = 1$</td>
<td>$k_d(J_i, J) = 2$</td>
</tr>
<tr>
<td>$k_d(J_i, J) = 2$</td>
<td>$k_d(J_i, J) = 3$</td>
</tr>
</tbody>
</table>

**Table 3:** Hamming distances from rational judgment sets to the profile from Table 2.

one $J_i \in J$ s.t. $k_d(J_i, J) = 2$. Thus we conclude that $J \in F^\max_{H}(J_\Delta)$ if $k_d = 0$.

Assume, without the loss of generality that $k_2 \geq k_3$, thus $D_m(J, J) = k_1 + 2k_2 + 1$. Observe that $k_1 + k_2 + k_3 = n$. Consequently, the larger the $k_1$, the smaller the $D_m(J, J)$ becomes. The judgment set with maximal $k_1$ is the one containing all the triples $(x_i, y_i, (x_i \land y_i) \rightarrow \varphi_i)$ for which $\varphi_i$ is in the maximally consistent subset in $\Delta$. □

**4.2 Geodesic distance aggregator**

The geodesic distance aggregator [9] is based on the geodesic distance $d_g$, that is defined as follows. Take an agenda $\Phi$ and an integrity constraint $\Gamma$. We then define the graph $G(\Phi, \Gamma) = (V, E)$ as follows. The set $V$ of vertices of $G(\Phi, \Gamma)$ consists of all complete and $\Gamma$-consistent judgment sets $J$, i.e., $V = \mathcal{J}(\Phi, \Gamma)$. Moreover, two vertices $J, J' \in V$ are connected in the graph $G(\Phi, \Gamma)$ if there exists no third vertex $J''$ s.t. (1) $J''$ is distinct from $J$ and $J'$, and (2) on each proposition $\varphi \in \Phi$, $J''$ agrees with $J$ or $J'$ (or both). The geodesic distance $d_g$ is then defined by letting $d_g(J, J')$ be the length of the shortest path from $J$ to $J'$ in the graph $G(\Phi, \Gamma)$. The geodesic distance aggregator $F^g_{g}(\Phi, \Gamma)$ or $F^g_{g}$ for short uses addition as its aggregator function $\ast$. That is:

$$F^g_{g}(\Phi, \Gamma) = \arg\min_{J \in \mathcal{J}(\Phi, \Gamma)} \sum_{J_i \in J} d_g(J_i, J).$$

For example, for the profile $J$ in Table 1 we obtain $F^g_{g}(\Phi, \Gamma) = \{q, p, r\}$. For intermediary steps of the calculation, the reader can consult [9], in particular, the last paragraph of the Section 3.1 there.

We show that the problem of computing outcomes for the judgment aggregation procedure based on the geodesic distance with addition as aggregator function is $\Theta^P_3$-complete.

**Lemma 2.** $\text{OUTCOME}(F^g_{g})$ is in $\Theta^P_3$.

**Proof.** In order to show membership in $\Theta^P_3$, we firstly show that the problem $\text{OUTCOME}(F^g_{g}, \Sigma)$ is in $\Sigma^P_3$ by describing a nondeterministic polynomial-time algorithm that has access to an NP oracle, and that decides $\text{OUTCOME}(F^g_{g}, \Sigma)$. The algorithm gets as input an agenda $\Phi$, an integrity constraint $\Gamma$, a profile $J$, two complete and consistent judgment sets $J, J' \in \mathcal{J}(\Phi, \Gamma)$, and
a number $k$. The algorithm guesses some natural number $0 \leq \ell \leq k$, many judgment sets $J_1, \ldots, J_\ell \subseteq \Phi$, and $\ell$ many judgment sets $J_1, \ldots, J_\ell$ such that $J_i$ is as well as $\ell$, for each $i \in [\ell]$. Moreover, it verifies (3) whether for no $0 \leq i \leq \ell$, there is some complete and consistent judgment set that lies between $J_i$ and $J_{i+1}$. It does so by querying the NP oracle whether there exists some set $J' \subseteq \Phi$ and some $i \in [\ell - 1]$ such that (a) $J'$ is a complete and $\ell$-consistent judgment set, and (b) for each $\varphi \in \Phi$, $J'$ agrees with $J_i$ or $J_{i+1}$ (or both). We know that condition (3) is satisfied iff the oracle answers “no.” The algorithm accepts iff all conditions (1)–(3) are satisfied. It is straightforward to verify that $\sum_{J \subseteq \Phi} |\mathcal{O}(J, J_i)| \leq k$ iff there exists some guess that satisfies conditions (1)–(3). Thus, $\text{OUTCOME}(\Phi)$ is $\Theta^p_2$-complete.

**Proof.** Membership in $\Theta^p_2$ is shown in Lemma 2. To show $\Theta^p_2$-hardness, we give a polynomial-time reduction from $\mathcal{QSAT} \cdot \mathcal{MAX}$-MODEL. Let $\varphi = \exists X. \forall Y. \psi$ be a true quantified Boolean formula, where $\psi$ is quantifier-free, and $X = \{x_1, \ldots, x_n\}$. We may assume without loss of generality that for each assignment $w : X \rightarrow \{0, 1\}$, we have $\exists Y. \forall X. \psi(w)$ is true. We construct an agenda $\Phi$ and a profile $J$ of the complete and consistent judgment sets $J_1$ selected by $F_\omega$ correspond exactly to the maximal models of $\varphi$. We define $m = 1$, and $w_0 = (m(1) - 1)$, and we introduce auxiliary variables $z_i$ for each $i \in [m]$. Intuitively, for each $i$, the variables $z_i$ will act as a cluster of switches, that can be triggered individually (and in several cases, collectively). We then construct the propositional formula $\chi = \psi \rightarrow \bigvee_{i \in [m]} x_i$, where for each $i \in [m]$ we let $x_i = \bigwedge_{j \in [m]} z_j \land \bigwedge_{l \in [m]} z_l$. We define $\chi$ such that whenever $\psi$ is true, that holds the switches $z_i$ are “on” for exactly one cluster.

We now define the agenda $\Phi$ by letting $\Phi = \{x_1, \ldots, x_n\} \cup \{z_i : i \in \Omega, j \in [m] \} \cup \{z_i \}$. Moreover, we let $\Gamma = \Gamma$. For the sake of convenience, we will introduce the following proper $Q$. We say that a complete and consistent judgment set $J \in \mathcal{J}(\Phi)$ has property $Q$ if there exists some $i \in [m]$, $t \in \Omega$, and $z_i \in [m]$, such that for each $i' \in [m]$, $t' \neq i$ holds that $\{z_i, \ldots, z_{i'} \} \subseteq J$. Because $\exists Y. \forall X. \psi(w)$ is true for each assignment $w : X \rightarrow \{0, 1\}$, it is straightforward to verify that each $J \in \mathcal{J}(\Phi)$ belongs to exactly one of three classes (A)–(C), defined by the following conditions: (A): $z_i \in J$ and $J$ has property $Q$; (B): $z_i \in J$, $J$ does not have property $Q$, and $J \cup \neg \psi$ is satisfiable; and (C): $z_i \in J$, and $J$ does not have property $Q$.

Next, for each $i \in [m]$, we define the complete and consistent judgment set $J_i = \{x_1, \ldots, x_n, z_i \}$, a number $k$. The algorithm guesses some natural number $0 \leq \ell \leq k$, many judgment sets $J_1, \ldots, J_\ell \subseteq \Phi$, and $\ell$ many judgment sets $J_1, \ldots, J_\ell$ such that $J_i$ is as well as $\ell$, for each $i \in [\ell]$. Moreover, it verifies (3) whether for no $0 \leq i \leq \ell$, there is some complete and consistent judgment set that lies between $J_i$ and $J_{i+1}$. It does so by querying the NP oracle whether there exists some set $J' \subseteq \Phi$ and some $i \in [\ell - 1]$ such that (a) $J'$ is a complete and $\ell$-consistent judgment set, and (b) for each $\varphi \in \Phi$, $J'$ agrees with $J_i$ or $J_{i+1}$ (or both). We know that condition (3) is satisfied iff the oracle answers “no.” The algorithm accepts iff all conditions (1)–(3) are satisfied. It is straightforward to verify that $\sum_{J \subseteq \Phi} |\mathcal{O}(J, J_i)| \leq k$ iff there exists some guess that satisfies conditions (1)–(3). Thus, $\text{OUTCOME}(\Phi)$ is $\Theta^p_2$-complete.

**Theorem 4.** $\text{OUTCOME}(\Phi)$ is $\Theta^p_2$-complete.

**Proof.** Membership in $\Theta^p_2$ is shown in Lemma 2. To show $\Theta^p_2$-hardness, we give a polynomial-time reduction from $\mathcal{QSAT} \cdot \mathcal{MAX}$-MODEL. Let $\varphi = \exists X. \forall Y. \psi$ be a true quantified Boolean formula, where $\psi$ is quantifier-free, and $X = \{x_1, \ldots, x_n\}$. We may assume without loss of generality that for each assignment $w : X \rightarrow \{0, 1\}$, we have $\exists Y. \forall X. \psi(w)$ is true. We construct an agenda $\Phi$ and a profile $J$ of the complete and consistent judgment sets $J_1$ selected by $F_\omega$ correspond exactly to the maximal models of $\varphi$. We define $m = 1$, and $w_0 = (m(1) - 1)$, and we introduce auxiliary variables $z_i$ for each $i \in [m]$, and each $j \in [m]$. Intuitively, for each $i$, the variables $z_i$ will act as a cluster of switches, that can be triggered individually (and in several cases, collectively). We then construct the propositional formula $\chi = \psi \rightarrow \bigvee_{i \in [m]} x_i$, where for each $i \in [m]$ we let $x_i = \bigwedge_{j \in [m]} z_j \land \bigwedge_{l \in [m]} z_l$. We define $\chi$ such that whenever $\psi$ is true, that holds the switches $z_i$ are “on” for exactly one cluster.

We now define the agenda $\Phi$ by letting $\Phi = \{x_1, \ldots, x_n\} \cup \{z_i : i \in \Omega, j \in [m] \} \cup \{z_i \}$. Moreover, we let $\Gamma = \Gamma$. For the sake of convenience, we will introduce the following proper $Q$. We say that a complete and consistent judgment set $J \in \mathcal{J}(\Phi)$ has property $Q$ if there exists some $i \in [m]$ such that for each $i' \in [m]$, $t' \neq i$ holds that $\{z_i, \ldots, z_{i'} \} \subseteq J$. Because $\exists Y. \forall X. \psi(w)$ is true for each assignment $w : X \rightarrow \{0, 1\}$, it is straightforward to verify that each $J \in \mathcal{J}(\Phi)$ belongs to exactly one of three classes (A)–(C), defined by the following conditions: (A): $z_i \in J$ and $J$ has property $Q$; (B): $z_i \in J$, $J$ does not have property $Q$, and $J \cup \neg \psi$ is satisfiable; and (C): $z_i \in J$, and $J$ does not have property $Q$.

5. RELATED WORK

The problem of finding the collective judgment sets has been approached by formulating various decision problems. One decision problem that has been studied is the following: given a judgment $\varphi$, a profile of judgments $J$ and
an aggregation function \( f \) is it true that the judgment \( \varphi \) is in all \( J \in f(J) \). In contrast, the decision problem studied by Endriss et al. [15, 14] is the same as we study it here. The class of distance based aggregators has been considered by Jamroga and Slavkovik [21], and they have shown that it is possible for the decision problem to be undecidable. In the literature [15, 14, 28], all of the better known judgment aggregation functions have been analyzed with the exception of the aggregators that we study in this paper. With this work, we thus—for now—complete the complexity analysis of the “winner determination” problem for the judgment aggregators considered in the literature.

It is well known that judgment aggregation generalises preference aggregation [7] and in particular that judgment aggregators generalise voting aggregators [27]. A preference aggregation problem is defined with a finite set of candidates \( C \) and a finite set of voters represented as total, strict and transitive preference orders \( \succ \), over the set of candidates. Such preference aggregation problems can be represented as judgment aggregation problems: the agenda \( \Phi_C \) is a set of issues \( xPy \), each interpreted as “alternative \( x \) is preferred to alternative \( y \)”, while the set of constraints is the transitivity constraint \( Tr \) expressing that you cannot have a judgment \( xPy \) and a judgment \( yPz \) without having a judgment \( xPz \), for any triple of alternatives \( x, y, z \). The voters can be represented as profile of rational judgment sets \( J_V \in \mathcal{J}(\Phi_C, Tr)^+ \).

It is interesting to compare the complexity results for the “winner determination” problem that we obtain with the complexity of the winner determination in the case of the respective preference aggregation methods. Dietrich [6] shows that the reversal scoring method generalises the Borda preference aggregation method [3], and also, as we discussed in Section 4, that \( F_d^\Sigma \) is a generalisation of the Kemeny method. The problem of checking if a candidate is a Kemeny winner for a profile of preferences is one of the first \( \Theta^2_p \)-complete problems, and here we observe no “complexity jump” when generalising the method to judgment aggregation. In contrast to its judgment aggregation generalisation, the Borda method is computationally easy, finding winners can be done in linear time of the number of agents and alternatives.

Interestingly, the \( F_d^\Sigma \) aggregator is also a generalisation of the Kemeny method. Let us construct the Hamming graph \( G(\Phi) = (V,E) \) where \( V \) is the set of all complete, but possibly inconsistent judgment sets from \( \Phi \) and there exists an edge in \( E \) between two sets \( J \text{ and } J' \) iff \( d_H(J,J') = 1 \). Observe that if \( G(\Phi) \) is s.t. every rational judgment set (node) in \( G(\Phi) \) is connected to at least one other rational judgment set in \( G(\Phi) \), then for every \( J, J' \in \Gamma(\Phi, \Gamma) \), we have that \( d_H(J,J') = d_\varphi(J,J') \). Now observe that the graph \( G(\Phi_C, Tr) \) for any set of alternatives \( C \) is a permutohedron with every node being connected to \( |C| - 1 \) nodes that are at Hamming distance one from it. Therefore, for any two judgment sets \( J, J' \in \mathcal{J}(\Phi_C, Tr) \), we have that \( d_H(J,J') = d_\varphi(J,J') \). Consequently for profiles \( J_V \) for the preference agenda it holds that \( F_d^\varphi(J_V) = F_\varphi(J_V) \). Thus \( F_d^\varphi \) would aggregate to judgment sets corresponding to preference orders that the Kemeny method would produce.

### Binary Aggregation

In addition to the judgment aggregation framework that we consider in this paper (as defined in Section 2), another framework has been considered in the literature to model judgment aggregation settings (see, e.g., [13, 17])—this other framework is known under the name binary aggregation (with integrity constraints). The main difference with the judgment aggregation framework that we consider in this paper is that no additional propositional variables (beyond those representing the issues) can be used to specify the logical relations between issues. In general, the complexity of the winner determination problem can differ between these two different judgment aggregation frameworks [15]. In particular, when considering the complexity from the more detailed perspective of parameterized complexity, complexity results tend to differ (see, e.g., [19]). All the membership results (for the classes \( \Theta^p_2 \) and \( \Theta_2^p \)) that we presented in this paper straightforwardly carry over to the setting of binary aggregation. The hardness proofs in this paper cannot all directly be used for the setting of binary aggregation. The reason for this is that transforming an agenda from the judgment aggregation framework that we use in this paper to the framework of binary aggregation, in general, leads to an exponential blow-up [13] (under some common complexity-theoretic assumptions). However, whenever the agenda \( \Phi \) used in a hardness proof contains all the variables occurring in \( \Phi \) as formulas in the agenda, the hardness proof carries over to the setting of binary aggregation. This is the case for our proof of Theorem 2, for instance. Extending the other hardness results that we obtained in this paper to the setting of binary aggregation remains a topic for future research.

### 6. CONCLUSION

We studied the complexity bounds of the winner determination problem in judgment aggregation for three aggregation methods so far unconsidered for such analysis in the literature: the reversal scoring rule and the two distance-based methods \( F_d^{\max} \) and \( F_d^{\Sigma} \). Judgment aggregation is a relatively new area of social choice and new methods for aggregating profiles of judgments are being actively developed, such as [4, 10, 16, 35] as well as other scoring methods given in [6], therefore we cannot claim to have closed the chapter on winner determination complexity analysis in judgment aggregation with our work. However, the methods we study here were the last of the methods frequently referenced in the literature for which a complexity analysis was not done.

We showed that the winner determination problem for the reversal scoring rule and \( F_d^{\max} \) is \( \Theta^2_p \)-complete, while that problem for \( F_d^{\Sigma} \) is \( \Theta^p_2 \)-complete. For judgment aggregation methods that satisfy non-dictatorship and the universal domain property, i.e., nontrivial methods that can aggregate any profile of rational judgment sets, the complexity of the winner determination problem has so far not been below the \( \Theta^p_2 \) level. We thus have a very strong indicator that the problem of aggregating judgments is computationally very hard. We do not yet have a clear picture of what the parameterized complexity landscape of this problem looks like, with the exception of the \( F_d^{\max} \) method studied in [19], nor how approximable this problem is for the various aggregation methods. These are immediate directions for future work.

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REFERENCES

[33] G. Pigozzi. Belief merging and the discursive dilemma:


