DISPUTE RESOLUTION WITH ARGUMENTS OVER MILESTONES: CHANGING THE REPRESENTATION TO FACILITATE CHANGING THE FOCUS

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Abstract: *The idea is to use a joint problem-solving representation rather than a payoff matrix formulation. We propose a novel representation where parties collaborate on achieving milestones with high probability. Unlike expected utility models, probability is used to guarantee transition from one milestone to the next. Arguments more easily occur over joint problem solving to provide stronger guarantees. Parties may still reject proposals but the language of the proposal, and the focus of the process, are altered to facilitate adversarial argument in the production of joint problem solving.*

1. Introduction

1.1. ODR

In harmony with wider changes in society – in particular the advances in technology and the large scale use of online services to transact all forms of business – recent developments in the field of online dispute resolution (ODR) have led to a new and deep interest in their use as one of the best alternatives to the trial in several law domains, like consumers and family disputes (originally, ADR, alternative dispute resolution).

ODR will help reduce obstacles to the good functioning of civil proceedings, negotiations and settlements, especially the cross-border ones, by enforcing a method that could improve agreements using processes that use argument to reach joint settlement. These areas include successions and trust and matrimonial regimes in a first stage, and later in other areas such as property and lease, company law and consumer law.

SquareTrade and other websites like Internet Neutral, WebMediate, and even Wikipedia have rule-governed processes and web-based forms to facilitate the resolution of disputes. AI and Law has published many contributions to e-Negotiation, from logics to systems, for over two decades.

It is the creation of e-procedure that triggers the engagement of a number of important legal and non-legal approaches. The first is the use of reason – let me persuade you that this is the way to settle (what Roger Fisher called «principled negotiation»). Many researchers have worked over three decades to deliver models of argument based on rules and precedents, and have applied these formalizable forms of argument to negotiation and appraisal of the relative desirability of outcomes.

However, to reach a solid agreement, engaged people need more than merely rational-economical forces. Eprocedures based on game theory principles of fair division and win-win solutions can be more satisfactory than using law principles, but AI ideas and representations can bring even more, much needed nuance.

1.2. Focus on Procedural Fairness

Fairness has usually been conceived either in terms of fair outcome distribution (distributive justice), or fair procedure (procedural fairness). For example, Last-Diminisher, Divider-Chooser, Taking-Turns, Selfridge-Conway, Moving-Knife, Lone-Chooser, and Adjusted-Winner can all be considered procedural prescriptions. (See Giacalone's dissertation, 2016.) Meanwhile, a meritocratic claim to justified inequality can occur in both the proportion of outcome, and the asymmetries of procedure. There are constraints as well as biases: We know from Rawlsian welfare economics that there may be a floor, from recent wealth-concentration concerns that there may be a ceiling. Professional sports rules for referees show us that there is a limit to the amount and timing of stochastics. Part of the justification of these procedures is that outputs are constructed upon participants' inputs.

Forcing simplicity on the description of outcomes has the effect of making dispute resolution difficult. This is easiest to see in zero-sum, tug-of-war situations where the logjam is broken by «logrolling.» In logrolling, loss in one dimension is exchanged for gain in another, to achieve agreement. This 2D solution is simply not visible when both players are fixated on one dimension. It is essential to «get the focus off the focus.»

Posing the problem mathematically often requires fixed dimensions, wheras the art of negotiation is often in seeing the other dimensions in which exchanges can be proposed, pushing out of the plane to expand the dimensionality of the zone of potential agreement.

1.3. Focus on Describing Outcomes

One promising thread of AI research on automated negotiation gives more attention to the outcome description, what is called the «object of value» in economics, rather than the mere process of agreeing and arguing.

Loui and Moore, in «Dialgoue and Deliberation,» suggested that game theory's bimatrix of utilities, where traditionally a single number for each «player» represented the value of an agreement, might be replaced with something more dynamic.

In the simplest example, a utility value would be replaced with a set of parameters for an optimization or search problem. The parameters would be fixed by agreement, such as the requirements in a Traveling Salesman Problem, but the agent's utility would be based on how much, how well, and how fruitfully the agent performed subsequent search. In this model, one may have appraisal estimates, but not final values, for settlements. An agent must search the space of what can be done with the settlement even as the negotiating agents search for a settlement.

That paper also discussed a more widely applicable representation. Many negotiation outcomes would replace the numeric utility value with a fragment of an AI plan, where action, contingent action, logical derivation of successor states (perhaps uncertain), and logical derivation of properties at states that might have value, all add complexity.

In many ways, the partial plan, or plan fragment, as an outcome of negotiation is a compromise between a legal contract and a decision tree or search tree, as one might expect.

A game theoretical model on its own is sometimes not enough for the ODR participants' needs. However, coupled with an AI model which could integrate features such as dialogue and possibility of reformulating there could be chances for ODR's rise.

1.4. New Objects of Value

In this paper, we propose an improved representation for the object of ODR. It is based on a new idea for the objects of value that specifically brings familiar risk analysis and decision theory ideas into the orbit of argumentation. It was originally intended to solve two problems in decision theory that result from too much simplicity in outcome representation.

The problem of short horizons, or «borrowing from the future,» appears in decision models primarily because it is hard to put value on streams of events. It is easier to define outcome states, to fix the horizon, assess utility synchronically, and ignore all pain and joy that precedes or follows. Utility theorists understood this from the start and took lotteries to be over objects as complex as the model needed to be. After the roulette wheel, the tax should be added.

This is nice in theory, but in practice, it is difficult to model past and future and bring utility to their appraisal. Moreover, as scenarios move further into the future, causality of action, enumeration of events, precision about probabilities, all turn from good guesses into pure fiction. Hence, decision models tend to have modest future envisionment. For dispute resolution, the same happens. Even if the language of an offer or settlement is precise with respect to important future events, the ability to put a utility value on the implied scenarios is beyond most reasonable people.

A different ontology for outcomes is needed: a structure that is fairly compact, but expandable; that succumbs to arguments over fairness or inadequacy, not just mathematical discount by probability; that admits imprecise but important valuable considerations; and that looks at a trajectory, not just a snapshot in time.

A new idea starts with a path of milestones that would be subject to pro-con argument, for the single agent. Here, the idea is extended naturally to pro-con argument among parties to a negotiation.

2. Mathematical Representation

A proposal is a set of commitments, some conditional, others compulsory, and a set of milestones (m1, …, mn) that define a trajectory. It is important to note that n is not fixed: in a single negotiation, some proposals may have one length and time step, while other proposals may refer to milestones at totally different times.

In the degenerate case, a trajectory is an end state and n=1, which is typical in game theory, decision theory, and much research on negotiation.

A set of transition probabilities link the milestones, pij, but the trajectory is a path, not a tree, so this is not a Markov model or other stochastic state-transition model. In the terminology of Herbert Simon, it might be an «aspiration,» or what AI might now call a planned path.

The probabilities are mainly used here to claim that each milestone is sufficient to make the next milestone probable (we will soon permit parties to argue over what is sufficient probability). In classic AI planning, deduction would require a probability of 1 for all transition probabilities. In decision theory, the probabilities would be less than 1, but each milestone would have multiple successors. This is of course too hard to model in practice beyond simple, encapsulated situations. In risk analysis, the probabilities are improved by adding commitments, usually best-effort mitigations, in the face of hazards. For negotiation, joint commitments will improve probabilities. «We both want the successor milestone, and I am willing to commit to a, so if you commit to b, the probability will be acceptably high.»

A set of identified events, Ev, with investment and response policy commitments from each participant, Inv and Resp, permits probability arguments for each transition probability. Probability arguments can be based on conditionalization, reference class considerations, or even judicial reasoning to a standard of proof, evidence or care. They need not be numerical probabilities because they will not be multipliers of utilities here. If one has the precision to do an expected utility calculation that can be accepted by all parties, that can be part of the description of a milestone, not its final valuation. Here, qualitative probabilities, from numerical ranges to values such as «more likely than not» can enter the model.

Attributes (or aspects, attainments) that have value can be attached as part of the description of the milestone, a(m) = (a1, a2, …, ak). These are collected as v(m) = (v1, v2, …, vk). Not all milestones will have the same attributes, nor even the same number of attributes that describe them. As the milestone extends further into the future, one would expect the attributes to be fewer. But some chance-qualification may simply change «has car» to «probably still has car». Here, qualitative objects of value, externalities, and ineffables can enter the model.

If one would like to theorize about multiple branches in a lottery, as one would in classical decision-theoretic representation of the future, one could set one attribute to be, e.g., 0.3-probability-of-payoff, and another attribute to be, e.g., 0.7-probability-of-loss.

Attitude toward risk would then enter the multi-attribute appraisal, to the extent that two values can be reduce to one. For some, 0.3-chance-at-positive-$100 and 0.7-chance-at-negative-$100 has the same value as $0; for some, it has the same value as negative-$40. Note that the case-based reasoning, or other argument-formation mechanism, is doing all of the work that microeconomics finds traditionally interesting. Rather than model risk precisely, it may be that an ADR process or ODR system simply judges certain lotteries to be «in bounds» and admissible in the sense of «fair, not foul,» and leaves further appraisal to the disputing parties. It may not be the job of the case-based projection to determine optimality, or right and wrong proposal, but simply that the proposal is not unfair on its face, by the standards of the arbiter.

We do not suppose that all k attributes carrying value can be so reduced. Chances mentioned in milestone descriptions are different from transition probabilities that provide guarantees of the connectedness of the trajectory. Remember that pij might often be simply «meets the standard required by this court.» Arguments for and against a trajectory take several forms:

(1) proposing a trajectory; (2) deriving parts of a description of a milestone; (3) adding to the considerations that describe a milestone; (4) adding to the hazards that might strengthen or weaken a transition probability; (5) giving a probability argument for a transition probability based on statistics, precedent, or statute; (6) arguing that the trajectory, taken as a whole, meets a fiduciary standard, a fair division, or an improvement over BATNA (best alternative to a negotiated agreement).

Arguments of types 1–3 are familiar to dynamic planning in AI (though unfamiliar to decision and game theory). Arguments of type 4 are inherited directly from risk analysis in reliability and safety engineering, as well as policy planning in management. Arguments of type 5 are familiar to certain kinds of non-Bayesians who construct probabilities directly from data, and even to some Bayesians and objectivist probabilists who can conceive of conflicting evidence. Type 5 arguments to a standard of proof, and type 6 arguments, are familiar to those who study case-based reasoning. Type 6 arguments could also yield to machine learning, especially for ADR/ODR. This is because typical settlement is just as meaningful in ADR as justified settlement. Machine learning projections can also carry normative force when the training examples are exemplary and the features are connected to principles. Another way that type 6 arguments can be made is through the construction of preference, or utility arguments.

The logical notation of the arguments is beyond the scope of this paper, and has been discussed thoroughly throughout the past decades of AI and Law.

3. EXAMPLES

3.1. One-Shot Tug of War

Before showing where this representation can be helpful, it is instructive to show where it is equivalent to classic outcomes.

Two parties are negotiating a price in a bazaar. The seller asks for 100Euro, while the buyer proposes 50€. There is one milestone, m1, with one attribute, price-paid(m1). Perhaps a new proposal makes a compromise on price: a1(m1) = 75€

Values are easily compared to reference objects or alternate scenarios. There are no transition probabilities, and k is fixed. So there is not much to argue about except the fairness of the proposal. Arg (Fair-Settlement(m1)) might be based on Arg(Typical-Settlement(price-paid(m1)) which might be based on prior cases, statistically or prototypically, with the usual defeasibility and specificity of generally similar, relevant, on-point prior cases.

3.2. One-Shot Exchange to Two Shot

An even better way to represent the same situation for the purposes of ODR would be to name the objects in the exchange: a1(m1) = semi-antique-Tabriz-3x5-area-rug; a2(m1) = 100€because by doing so, it becomes easier to create variations of the proposal:

a1(m1) = semi-antique-Tabriz-3x5-area-rug; a2(m1) = 50€-and-promissory-note

followed by a second milestone:

a1(m2) = semi-antique-Tabriz-3x5-area-rug a2(m2) = 50€-prior a2(m2) = 50€-at-this-later-time where there remains room to put a specific calendar timing on the second payment (and possible documentation of fulfilment of the promissory note).

3.3. Child Custody Example

A most important application of ODR is negotiation of child custody in family court. The tug-of-war typically occurs in the time-spent-with-child or present-at-holidays dimension, though support payment levels may also be subject to barter.

a1(m10) = roughly-equal-visitation-by-day; a2(m10) = roughly-equal-presence-at-holidays

The question might be how to achieve, ten years later, a rough equivalence of divided time (one might even be specific, such as no-more-than-10%-inequality).

Regardless of how the path sets out, there are clear hazards. A small event, such as a non-electively missed holiday, may be corrected with joint commitment to a response policy of trading the next holiday. This is a non-specific hazard, so there is a question of whether the analysis permits hypothetical events with responses that generalize from the specific to non-specific. One way to do the analysis is to create a milestone for the end of each year and give a specific anchored-by-year response commitment for each anchored-by-year hazard.

Event = cannot-do-holiday-in-year-3;

Response = swap-first-option-holiday-in-year-4.

Rather than subject the analysis to a generalization post-processing, to extract comprehensive non-specific agreements, we rely on the imagination of the participants to generalize in their own minds. What the dialectic permits us to do here is to respond to a specific argument, in this case a specific, hypothetical, calendar- or transition-anchored hazard, with a specific response commitment. An efficiency is achieved because the rebuttal need only respond to the counter, not to all similar counters at any other time.

Thus, the ODR process uses argument to achieve the bones of an agreement, not to flesh out the full body or text of the final agreement.

A much larger hazard is also hypothetical:

Event = parent-job-is-transferred-out-of-state; Response = transferred-parent-pays-plane-fares.

The transition probabilities may remain sufficiently high for reaching m10 as a path from (m1, m2, …, m10). But a reasonable rebuttal, again, possibly from the ODR AI or third-party arbiter, is the stress on the child, a3(m10) = reasonable-cumulative-stress-on-child which may force a reduction of aspiration from no-more-than-10%-inequality, to perhaps no-more-than-25%inequality.

In an ODR setting, many of the concerns and aspects will be known to the system, available in menus (or shared across cases, like prior search phrases), with prior case opinions on fairness. This is the AI analogue of actual family court settlement design space, where custody agreements are struck as variations on one another routinely.

3.4. Actual ODR Cases

Giacalone's recent dissertation on ODR looked at 300 cases of child custody. In his opinion, over 200 would have benefitted from the more complex representation described here, primarily because of the assignment of non-comparable items in family disputes. Cases turned on such things as

a) the approval of a separation agreement in time; b) the termination of a joint tenancy; c) the judicial separation; d) the division of multiple assets held as property; e) the judicial separation and restitution of defined goods; f) the division of defined goods and adequate compensation for indivisibles; g) the switch from a judicial separation to the approval of the separation agreement; h) the custody of a child.

Neither King Solomon nor family court can entertain fair-division divider-chooser strategies for all these aspects.

4. Discussion

4.1. Fiduciary Standards

Negotiation in the AI planning and discourse community is seen as joint problem solving. There, the problem solving is the same as the dialectic over events and commitments. We add another theme, which is the idea of co-piloting or team-shepherding a trajectory through a dynamic, even treacherous time-and-value terrain.

Far from the idea of a zero-sum game, where each side aspires to deny, in order to acquire, we choose a representation that asks participants to agree on aspiration, then bargain over how to make it possible.

The thinking is that each side should be bound as a fiduciary to the attainment of the milestones. Fair division is not so much about splitting the pie as it is about allocating and shouldering responsibilities, e.g., to guarantee that the pie is not left out in the rain. Especially since arguments from precedent are likely to reflect judicial opinion on standard of due care, parental, labor, or owner rights and responsibilities, rather than past frequencies, perhaps fiduciary standards are a good metaphor. Optimality certainly is not an appropriate metaphor.

4.2. Traditional Negotiation Ideas

One might ask what has happened to some traditional ideas that occur in game-theoretic conceptions of negotiation.

Where is equilibrium? There is a judicial background to the agreements, so self-enforcement is unnecessary.

Where is power resulting from having a good security (BATNA) position or a believable threat to walk away? Being well positioned to make a deal, or make a threat, is still present. That happens in the minds of the participants and is not modeled formally here. Our focus is on the object of the proposed agreements, and their appraisal on objective (third-party observer, rational persuasion, or principled negotiation) grounds. We have exchanged utility values in a game matrix for admissibility arguments over strands of partly specified paths into the future.

Even when a 1000-page contract is written, as a particular proposed agreement, that proposal sits within a zone of potential agreements, a process of choosing which proposals to make, each party's evaluation of the proposal relative to other perceived options, and so forth.

We have moved away from the concepts of ask, bid, and concession, i.e., price haggling, toward a kind of problem solving that leads specifically to joint protection and control of the envisioned, aspirational path.

As with most joint problem-solving dialogues, the pro-con process may be considered just «cheap talk» by economists, which perhaps shows how differently economists have approached negotiation. Focusing on a specific kind of dialogue, to produce arguments over shared fiduciary responsibility, reduces the risk of emotional distress often arising from less focused cheap talk.

4.3. Returning Attention to ODR Systems

Other ODR systems proposed in the literature can support logrolling as this representation does. There is probably little precedent for case-based scrutiny of a path. AI negotiation generally considers channelling discourse toward productive joint problem solving. This representation puts much more burden on the use of probability arguments, and joint problem solving associated therewith.

Instead of asking «HOW MUCH?» or «WHAT IF I WALK AWAY?» our system will tend to ask «WHAT ELSE MATTERS TO YOU?» «WHAT DO WE WANT TO HAPPEN NEXT?» «HOW CAN WE MAKE THAT HAPPEN?» «WHAT CAN JEOPARDIZE THAT FROM HAPPENING?» «WHAT STRONGER GUARANTEE CAN BE MADE WITH A CONDITIONAL COMMITMENT OR UNCONDITIONAL INVESTMENT?» Those are the variations on a proposal most easily represented here.

Instead of saying «THIS BUNDLE IS WORTH $x» or «THIS LOTTERY IS WORTH $y», the system will naturally ask «HOW CAN THIS MIX OF ATTRIBUTES BE IMPROVED?» perhaps «AT THIS TIME» or «AT A LATER TIME». The argumentation is focused on the question of «IS THIS MIX OF ATTRIBUTES ADMISSIBLE?» i.e., to a third-party arbiter, or given precedent similar settlement. It places the focus on arguing that «THESE COMMITMENTS MEET THE REQUIRED FIDUCIARY STANDARD FOR TRAJECTORY LIKELIHOOD» rather than «YOUR PROPOSAL IS UNACCEPTABLE».

The artificial intelligence picture of the agent will be preferred to the game theoretic one in the modelling of interactions in direct proportion to the extent to which knowledge informs creativity. The main difference is that AI's models consider topics such as planning, knowledge representation, automated reasoning and argumentation as a separate field of study. Can any of these pieces help facilitate, even automate, creativity in negotiation?

The drawback of game theory's models starts with the fact that – compared to AI's models – they seek to explain settlements in a static problem formulation with static valuations of proposals. The key point is that negotiation includes more important phenomena such as dialogue, planning, focusing and reformulating. The aim of an AI model deployed in ODR is of fitting all the pieces together, with a better design space for proposals.

Many disputes have multiple components and without sophisticated tools to deal with the inherent complexity, decision-makers are forced to deal with issues one at a time. A piecemeal approach to negotiation encourages positional rather than mutual gains bargaining. Various issues and outcomes may lead negotiators to make decisions based on psychological dynamics and emotion rather than reason.

Moreover, reasonable outcomes are compromised when decision-makers make logic errors, take short-cuts, or permit emotions to get the upper hand when under the stress of intensive negotiations. Without properly assessing the risks, parties are often unrealistically confident of a favourable outcome, should the matter be taken to court.

Leaving the old idea of utility as an archaic measure of the intensity of preference, and admitting ideas from AI, generally, and AI and Law, specifically, brings new opportunity. A whole category of disputes currently not being considered for ODR may become appropriate for application of comprehensive e-negotiation systems, such as family disputes, with more attention paid to controlling trajectories instead of fighting over portions.

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