# **HOW TO MEASURE FAIRNESS IN NEGOTIATIONS?**

Investigation of the fairness metrics in automated negotiations

### BACKGROUND & MOTIVATION

- Due to advancements in collaborative AI, there is a shift from human to automated agents in negotiations
- We want to measure 'fairness' in the automated negotiations to ensure that they are conducted justly
- However, fairness is a broad concept, that philosophers and psychologists discussed throughout the ages
- There is no one generally agreed on framework on how to measure fairness in automated negotiations

## **2. RESEARCH QUESTION**

- What are possible ways to measure fairness in automated negotiation, and which are best suited for this problem?
  - What are areas within negotiations in which fairness can be investigated?
  - How can we assess which fairness approach is best suited for automated negotiations?

### **3. FRAMEWORK**

#### **Fairness Issues by C. Albin:**

- Structural protocol, relations between parties
- Process agents' behaviour during the negotiations
- Procedural strategies used in the negotiations
- Outcome final allocation in the negotiation

#### **Investigated Fairness Metrics:**

- to bargaining Distance problem allocation solutions (J. Nash, 1950)
  - Nash Product, Kalai-Smodrinsky
- Sum of individual utilities
- Fluctuations in final outcome allocation (Dwork et al., 2012)
- Kindness Function (Rabin, 1993)
- Needed time to agree (Sanchez-Anguix et al., 2021)



### $\pi_2(b_2, a_1) - \pi_2^e(b_2)$ $f_1(a_1, b_2) =$

## **4. METHDOLOGY & EXPERIMENT SETUP**

Compare how fairness metrics assess eccentric parties and fairnessoriented parties develop using GeniusWeb framework **Eccentric Agents**:

- Hardliner
- Random Walker
- Simple-time Dependent (Boulware, Linear, Conceder)

### **Experiment Setup:**

### **5. RESULTS**

	Distance to Nash Point	Distance to Kalai-Smodrinsky	Sum of Utilities	Distance to Maximal Utilities Sum Point	Standard Deviation	Standard Deviation in Utility 2	Mean Kindness	Kindness per	Mean time
Hardliner (E)	0.257	0.302	1.060	0.217	0.179	0.154	-0.061	-0.00031	194.2
Random Walker (E)	0.131	0.173	1.070	0.250	0.099	0.089	0.307	0.01065	28.9
Boulware (E)	0.157	0.205	1.080	0.165	0.115	0.102	0.063	0.00046	137.2
Linear Concsession (E)	0.142	0.205	1.085	0.157	0.099	0.094	0.124	0.00143	86.6
Conceder (E)	0.155	0.200	1.088	0.180	0.124	0.115	0.170	0.00379	45.1
Tit-For-Tat (F)	0.129	0.140	1.070	0.240	0.100	0.090	0.292	0.00156	187.1
Non-monotonic (F)	0.137	0.183	1.091	0.179	0.120	0.112	0.129	0.00146	151.7

## **6.** CONCLUSION & FURTHER EXTENSIONS

**Kindness Function** 

#### **Fairness-oriented Agents:**

- Non-Monotonic Concessiosns Agent
- Tit-for-Tat Agent

e1 = 0.5, e2 = 2 ---- e = 1.0 e = 2.0 e1 = 2.0, e2 = 0.5 0.0 0.4 0.6 Normalized Time Negotiation traces 0.7 1 0.6 Agent 1 trace Agent 2 trace Pareto frontie Nash product 0.5 0.6 0.7 0.8 0.9 Utility 1

Non-Monotonic Time-dependent concession strategie

• Twenty double round-robin tournaments with bilateral Negotiations under Stacked Alternating Offer Protocol with 200 rounds deadline • Bidspace of ten million complete bids in Linear Additive utility domain • Frequency-based Opponent Modeling with Laplace Smoothing • Acceptance Criteria based on the utility of next offered bid

• Aggregate results from the tournament have been categorized by fairness metrics of Distance to Bargaining Problem Solutions, Sum of Individual Utilities. Fluctuations in final allocation, Kindness function & Needed time to agree

• The most consistent individual Fairness Metrics have been Distance to Bargaining **Problem Solutions**, especially distance to Kalai-Smodrinsky point

• There is some risk of potential error in using individual metrics thus using a combined model with interdependence between the fairness metric would be better, e.g. Machine Learning & Neural Network, Regression-Based categorization

• Further research extension could consider extending the set of negotiation agents, using different domains, and allowing agents to learn throughout the tournament. A



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