TRADING AGENT COMPETITION SPECIFICATION

v1

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Fetch.AI

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Contents

1 Introduction

This document is a specification for the Trading Agent Competition (TAC) framework. It accompanies the public release of our TAC python package, an open source implementation of the specification by Fetch.ai. The release of this framework also coincides with the first competition under the TAC framework organised by Fetch.ai.

The purpose of this, and any future competitions under the TAC framework, is to foster a developer community around Fetch.ai's ecosystem, and to excite developers with the potentials of building on, and interacting with its various technologies, including the OEF, and later on, the ledger.

Our aim is to design competitions that resemble real applications of Fetch.ai's current or future technology. In other words, the scenarios designed for each competition will have strong ties with the experience of building on or using Fetch.ai's systems. As such, our hope is that through the competitions, participants will gain familiarity with using the various components of Fetch.ai's technology, and are introduced to its different use cases.

The vision for the first competition is to deliver a multi-agent competition that ignites excitement with respect to agent development. The competition is for anyone with an interest in creating agents on Fetch.ai's platform, including casual and experienced developers, researchers, and those interested in Fetch.ai's vision of a decentralised economy. No limit is placed on the number of participants and the type of teams. For the first competition, an in-person event, similar in form to a Hackathon, will take place in which, as well as being able to compete, participants would have the chance to meet and engage with some of Fetch.ai's team members. For the future, our aim is to enable everyone to participate in the competitions fully remotely, with some competitions having an associated in-person event organised simultaneously for added engagement.

It has been of great importance for us to ensure the competition has a low barrier to entry while offering a rich domain with vast opportunities for innovative solutions. For instance, there will be a number of easily configurable, so called *baseline agents* provided by Fetch.ai, which could be fine-tuned with minimal modifications to get the desired behaviour, or extended with in-depth functionality.

The winner and runner-up teams in the competition will win FET tokens. Note that the detail of the competition, including date and time, the competition's format, prizes, and the venue for the in-person event, will be specified in this link.

Replace this, and all the links with the actual address.

2 Competition

2.1 Target audience

The competition is designed with the following audience in mind:

- Individuals with minimal coding/development skills but with expertise or interest in some other area related to the trading agent competition (e.g. those with expertise in economy, finance, trading, multi-agent systems, agent strategy, etc).
- Casual developers interested in agent development.
- Seasoned software engineers interested in agent development.

2.2 Scenario

As this is the first competition under the TAC framework, we decided to focus on a scenario that involves one of the most fundamental forms of economic interactions; bilateral trades. The competition involves a society of agents, each starting with a number of goods. The agents can engage in one-to-one trades using simulated FET tokens as the medium of exchange.

Each agent, in the real world, would represent an individual or a group of people (e.g. a family) who is tasked with looking after their interest by maximising their welfare. In order to be able to do that, the agents would be made aware of their owners' preferences and values. In the competition, this is simulated by explicitly giving each agent a representation of their owners' preferences over goods at the beginning of a round. During the competition, the goal of each agent is to maximise its owners' interests by engaging in profitable trades, of course taking into account their preferences.

For those who prefer a tangible story, consider the following:

There are a number of different live performances in a festival that is coming up. Due to high demand and limited availability of space, the organisers of the festival have decided to use the following system for registration and ticketing. Every group of people who plan to attend the festival (e.g. families, groups of friends) must be represented by one computational autonomous agent who handles their registration and ticketing on their behalf. The agents should register the group of people they represent for the festival, at which point through lottery, each agent will be given a number of tickets at random to each performance.

Of course each participant has varying preferences towards the different shows, which may certainly be different to the other participants. Each agent is assumed to be aware of the preferences for the the group of people they represent. However, crucially an agent does not know the preferences of other groups as represented by other agents. Once all the agents receive their tickets, they are given some time to gather the best combination of tickets for their own respective group, by trading tickets with other agents. The trades are bilateral (i.e. one to one) and using simulated FET tokens as the medium of exchange. At the end of this time period, agents are evaluated based on how well they have satisfied the preferences of the people they represent through trade.

In the next section, the setup of the competition is more formally defined.

2.3 Setup

(**Agents**) There is a set A of agents partitioned into $A_{external}$ and $A_{baseline}$, i.e. $A = A_{external} \cup A_{baseline}$. Each agent $a \in A_{external}$ is provided by a competition participant. Each agent $a \in A_{baseline}$ is an instance of one of the baseline agents created by Fetch.ai. Note that $A_{baseline}$ can be empty, since it only serves the purpose of providing sufficient agent numbers during a competition, and for agents to train against during training. The game assumes a minimum number of agents min_agent (see Section 2.5 for more details on this). Finally, there is a special agent c, called the *controller agent*, which runs the competition, and due to its special role, is not included in A. Section 3.3 describes this agent in more detail.

(**Goods**) There is a tuple of n sets of goods $X = \langle X_1, \ldots, X_n \rangle$ where each i $(1 \leq i \leq n)$ represents one type of good (e.g. festival ticket to a concert by Elton John) and each element of the set X_i is an instance of that good type (e.g. equivalent instances of festival tickets to an Elton John concert). In general, we may have $|X_i| \neq |X_j|$ for any two $i, j \in \{1, \ldots, n\}$ where $i \neq j$; that is, the number of available good instances could be different for two different goods. As a consequence, we may in general have differing aggregate supply across goods.

(Endowments) Agents are provided with *endowments*[1] in the goods. That is, each agent $a \in A$ has an endowment $e^a = \langle e_1^a, \ldots, e_n^a \rangle$, a tuple of length n, where the set $e_i^a \subseteq X_i$ is the endowment of agent a in good i. Each agent is given at least some $base\_amount$ of each good, thus for any $1 \leq i \leq n$, $|e_i^a| = \{base\_amount, \ldots, |X_i|\}$. We assume that endowments are allocated such that for each $i \in \{1, \ldots, n\}$ we have $\bigcup_{a \in A} e_i^a = X_i$; that is, all endowments for a good sum to the total instances of that good. Finally, every agent is endowed with the same $money\_amount$, a positive real number.

(Current holdings) Each agent a's *current good holdings* are denoted by $x_i^a \subseteq X_i$. Therefore, $|x_i^a| \in \{0, \ldots, |X_i|\}$ (note how agents can have no instance of a good i at some point in time but never a negative amount). It must be the case that for each $i \in \{1, \ldots, n\}$ we have $\bigcup_{a \in A} x_i^a = X_i$; that is, all of the agents' current good holdings of a given good sum to the total instances of that good available. We further denote $x^a = \langle x_1^a, \ldots, x_n^a \rangle$. Each agent a's *current money holding* is denoted by m^a and it must always be the case that $\sum_{a \in A} m^a = |A| \times money\_amount$ and for each agent $m^a > 0$.

(Preferences) Agents are assigned *preferences* for goods and money by the controller c. That is, each agent $a \in A$ has a preference relation $\preccurlyeq_a$ across goods which totally ranks any possible combination of good bundles. Preferences are assumed to be transitive, thus for any three arbitrary goods x, y and z, $x \preccurlyeq_a y$ and $y \preccurlyeq_a z$ means $x \preccurlyeq_a z$. In practical terms, this means each

[1]An endowment is a subset of the good instances assigned initially to an agent.

agent a has the same utility function u^a which is quasi-linear[2] in goods and money:

$$u^a(x^a, m^a) = m^a + g(x^a) = m^a + \sum_{i \in \{1,\dots,n\}} s_i^a \times f^a(x_i^a)$$

such that

$$f(x_i^a) = \begin{cases} \ln(x_i^a) & \text{if } x_i^a > 0 \\ -1000 & \text{otherwise} \end{cases}$$

and where $s_i^a > 0$, and for all i, a:

$$\sum_{i \in \{1,\dots,n\}} s_i^a = 1$$

Hence, each agent a's preferences are represented by the vector s^a. This means, we are implementing the well studied Cobb-Douglas function for $g(x^a)$ which has the gross-substitutes property. This property ensures that our game has in fact a unique equilibrium (under some assumptions, like if transaction costs are zero)[3]. In the interest of tractability and to guarantee an equilibrium, it limits preferences in that goods cannot be complements.

Add references or web links for the Cobb-Douglas function and the gross-substitutes property

(Trade cost) We introduce a *cost to trade* k to explicitly model transaction costs that would eventually occur on the ledger. This has the nice side effect that it limits against some forms of DOS (provided the attacker cares about winning the competition). Each transaction incurs the same cost k.

[2]see `https://en.wikipedia.org/wiki/Quasilinear_utility`

[3]In particular, this competitive equilibrium is achieved via a so called *Walrasian auctioneer* described here.

2.4 Discussion

The setup mirrors a Walrasian Exchange Economy which is the workhorse model in economics for representing a market. It demonstrates well the concepts of allocative (/Pareto) efficiency (e.g. allocating resources to those who will make best use of them). An excellent introduction to the economics of this Exchange Economy is provided here.

Since agents negotiate one-on-one, they should not be able to achieve the efficiency of the Walrasian Exchange Economy. In particular, it has been shown that in theory, an auction is more efficient than negotiation under most circumstances (see here). This does not mean that individual agents won't be able to outperform through negotiations relative to an auction based market outcome. In particular, due to the private information on preferences and good holdings there is vast scope for some agents to perform better than others not by chance alone.

Note that from a game-theoretic perspective, the competition is not a zero-sum game. That is to say, an increase in one participant's score is not necessarily - and in general unlikely - at the cost of another. Therefore, opposition is weak in this setup since trades could potentially be beneficial to all parties involved.

Agents' preferences and endowments are provided exogenously by the controller. In a real-world use-case the preferences and endowments would arise naturally. However, for a competition it is necessary to impose these on the agents to guarantee an interesting and fair setup.

Agent's treat goods independently. However, for a hyper-rational agent price changes in one good should lead to changes in demand for the other goods due to the gross-substitutes property.

2.5 Trading game phases

Pre-trading game phase:

- A trading game G consists of k game instances g, i.e. $G = \{g_1, \ldots, g_k\}$.
- Agents register with competition controller during time $T_{registration}$.
- If the minimum threshold min_agent of registered agents is not met, then the competition manager will spawn a number of baseline agents $a \in A_{baseline}$ to meet the minimum threshold, i.e. until $|A| \leq min\_agent$. This is to ensure there are enough trading partners/options for each agent.

Each trading game instance g:

- A game instance lasts for time $T_{instance}$.
- A new draw of endowments and preferences for each agent is made by the game controller. This is to take account of differences in agent preferences and endowments excessively impacting the winner selection.
- Agents query their endowments and preferences from the game controller.
- Agents trade with each other (i.e. they are simultaneously the buyer and the seller of some good):
  - Trades need to be registered with the competition controller to be considered valid. The competition controller can be thought of as replicating a smart contract on a ledger.
  - Trades are bilateral (i.e. one-to-one).
- After time $T_{instance}$ has passed the league table of the trading

game instance g is identified by the game controller. Note, it still has to be established whether this information can be shared with agents at this point.

- At the end of a game instance a pause is taken which lasts for time T_{pause}.

Post game phase:

- The competition manager will report the final league table by averaging across all game instance league tables.

The competition will take time $T_{registration} + [k \times T_{instance}] + [(k-1) \times T_{pause}]$.

3 TAC Components

3.1 Code Development Objectives

When we set out to develop TAC, we determined a number of design objectives:

- Developers should be able to extend baseline agents.
- Developers should be able to easily swap out components of baseline agents.
- Competition organisers should be able to easily adjust the game configuration.
- Agents should be able to make all decisions autonomously.
- The controller should mirror a smart contract and eventually be implemented in a smart contract on our ledger.
- References in agents, communications, and objects should be as explicit as possible, e.g. to any data models, ontologies,

protocols and languages used.

- The agent architecture should logically separate the agent's strategy (i.e. its decision making component), protocol adherence (i.e. units that ensure the agent's behaviour complies with protocols) and beliefs (i.e. the agent's internal belief about the the state of the world).
- Agents should be proactive or reactive at the choice of the developer.
- A key focus of the python package development is to ensure that both the competition framework and the agent framework allow for high modularity and composability. As we move towards more sophisticated architectures we will move closer towards achieving this goal. The community is invited to contribute to our framework development.

3.2 Network Environment

Early competitions will be held in a common identity managed environment. Fetch.ai will host the environment - consisting of *OEF node*(s), a competition manager - called controller - and a set of baseline agents - and make it accessible via the web. A KYC provider will vet each participant which will allow us to provide environment access credentials to the competition participants. As Fetch.ai is moving towards deploying its ledger main-net, we will decentralise more and more aspects of the competition management, with the vision that eventually anyone could implement their own agent competition subject to their own specification.

The OEF nodes come with the *OEF* functionality. One such functionality is message relaying. This means that through appropriate APIs, agents could send and receive messages to each other, and the OEF will handle the low level delivery of the messages over the underlying network.

The environment will also be made available as a sandbox on a Docker image. The sandbox will be modular and configurable. The host of the sandbox will be able to configure the competition metrics (e.g. endowment and preference generators, $T_{registration}$, $T_{instance}$, T_{pause}). A sandbox can then be run a) without adding any agents, in which case a number of baseline agents will compete with one another, b) with a mix of baseline agents and custom agents from the developer, or c) with no baseline agents and only agents from the developer. The agents provided by the developer connect to the sandbox via a port.

3.3 Controller

Fetch.ai is progressing towards launching a distributed ledger system.[4] The ledger is a secure, decentralised mechanism for storing and keeping track of information, such as the transaction history of agents in the competition. Furthermore, the smart contract functionality of the ledger, amongst other things, could be used to run and manage the competition.

Due to the ledger's absence in the current competition, a special controller agent c takes on the dual responsibilities of transaction settlement and competition management. This effectively means that the controller agent is the only entity that will hold the global state of the competition. Therefore, all participating agents must register their transactions with the controller agent for those to be considered valid.

Furthermore, the controller is responsible for generating the

[4]Details of this could be found on www.fetch.ai.

endowments and preferences of all agent at the beginning of each game instance, ensuring that they are somewhat orthogonal. This is implemented through a *generator* algorithm in the game controller which acts as the random seed to each game instance.

To summarise, the controller agent's responsibilities are as follows:

- At the beginning of each round, the controller agent generates and assigns the endowments e^a and preferences s^a of every participating agent a.
- During each round, the controller agent registers and settles transactions, ensuring the feasibility constraints listed in *current holdings* in Section 2.3 are met. This means that the controller agent essentially keeps track of the current good and money holdings of every participating agent during the course of the competition.
- At the end of the competition, the controller agent constructs a league table containing the final scores and ranking of all participating agents.

3.4 Baseline agents

3.4.1 Reactiveness vs Proactiveness

When designing an agent, it is important to pay close attention to the environment in which the agent will eventually be deployed. This is because the nature of the environment often imposes certain requirements on the characteristics of the agents which are to 'live' in the environment while successfully meeting their design objectives.

Of such characteristics, two of the most fundamental ones are *reactiveness* and *proactiveness*. The first refers to an agent's ability to respond to changes in the environment. For example, an agent responsible for controlling the central heating/cooling system of a house has to be capable of reacting to changes in the temperature of the house, and act accordingly.

On the other hand, proactiveness refers to an agent's goal-oriented tendencies. A proactive agent always has some state(s) of the environment in mind (i.e. its goals) which it tries to achieve through a, perhaps complex, series of actions (i.e. a plan), either individually or by cooperating with others.

Note that it is not difficult to create purely proactive agents. Such an agent would fixate on a goal state, and if the pre-conditions of its plan of action are met, executes its plan, after which it expects to have achieved the goal state, in other words satisfying the post-conditions of its plan. In systems where the environment does not change, a purely proactive agent may be sufficient. However, in environments which are dynamic, i.e. where the environment constantly changes, multi-agent, whereby other agents also make changes to the environment, or complex/uncertain, where it is difficult for the agent to fully observe the environment, a purely proactive agent would fail. For instance, when the preconditions of a plan suddenly becomes false while the plan is being executed, or when a goal state, i.e. the reason for executing the plan, is not valid anymore, then there would simply be no reason to continue executing the plan.

It is equally easy, and to a similar extent ineffective, to create purely reactive agents that just respond to the environment. What is desirable is striking an effective balance between proactiveness and reactiveness; agents that move systematically towards achieving their goals, while constantly evaluating their goals and plans, responding to any change in the environment that affect these, in time for their reaction to be of value.

Typically in multi-agent systems, incoming events that an agent has to respond to take the form of messages that it receive from other agents in the environment. These messages might range from requests for specific resources the agent offers, to broadcasts that a specific public contract was created, to regulator agents informing the agent that its actions may have breached the environment's protocol.

The baseline agents provided by Fetch.ai are designed to exhibit goal-oriented behaviour while having the capability to react to changes in the environment. From a technical perspective, the agents have a so called *main loop* and an *event loop*. The former controls the agent's proactive behaviour, where at each 'tick' of the loop, the agent moves towards achieving its goal. The event loop on the other hand is responsible for processing incoming events. In our implementation, incoming events (i.e. messages) are placed in a queue by the event loop, which can then be processed in the main loop.

More specifically, the main loop in a baseline agent ticks every (say) 10th of a second, where each time through the loop it:

1. Processes any incoming messages.
2. Updates the agent's internal state.
3. Allows the agent to make decisions and act.
4. Waits until it is time to "tick" again.
5. Goes to 1.

The key is to ensure that any message handling and internal state update happens fast enough to always (or mostly) avoid going over the allowed tick duration (e.g. 10th of a second). The benefit would then be that the whole process could be kept single threaded and the code straightforward to read. If there is a need for some heavy processing, then there are a few options:

- Splitting the task up into chunks and processing them over several ticks (storing any intermediate internal state).
- Making the tick duration longer.
- Using language specific features (e.g. co-routines in python).
- Splitting the process across different threads, having the main thread just wait until all threads are finished with their job.

3.4.2 Baseline Agent with no world model

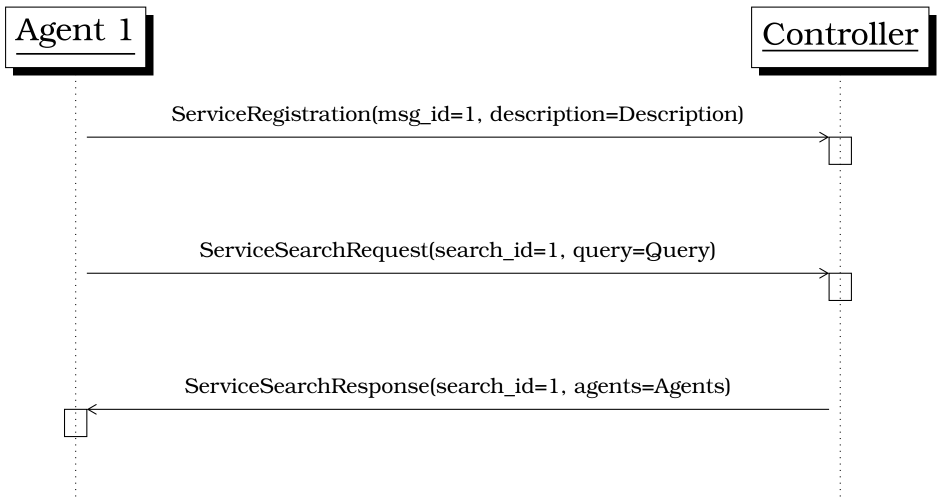
This is the most basic baseline agent developed by Fetch.ai that is able to compete.

A baseline agent without a world model $a \in A_{baseline}$ will rank her goods according to her preferences $\preccurlyeq_a$. She will then offer to sell an instance of her current holdings in good i (i.e. x_i^a) at a price p *equal* to her marginal utility for i (i.e. $p \geq s_i^a$) given her current good holdings. She will accept any request for sale of good i at a price p *equal to or less than* her her marginal utility for i (i.e. $p \geq s_i^a$) given her current good holdings. Similarly, she will offer to buy an instance of good i at a price p *equal* to her marginal utility for i (i.e. $p < s_i^a$) given her current good holdings. She will accept any request for purchase of good i at a price p *equal to or less than* her her marginal utility for i (i.e. $p \geq s_i^a$) given her current good holdings.

In the following sections we describe the negotiation as well as search and discovery process implemented by the baseline agent.

The register and search:

Figure 1: A sequence diagram of a service registration and service search.



Agent 1
Controller
ServiceRegistration(msg_id=1, description=Description)
ServiceSearchRequest(search_id=1, query=Query)
ServiceSearchResponse(search_id=1, agents=Agents)

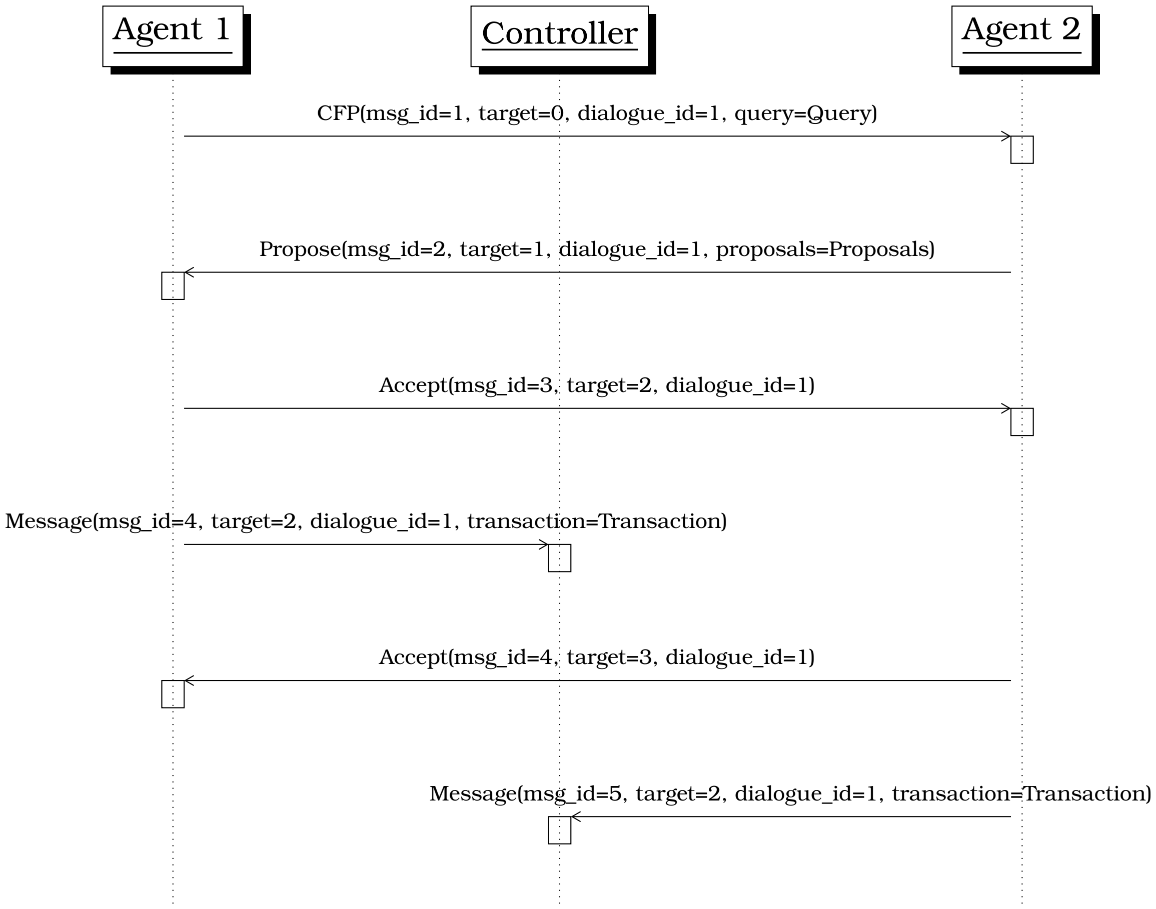
The negotiation protocol follows the FIPA specification. This means, there is a multi-step dialogue during which agents negotiate. We describe this in detail below.

The second Accept is what we refer to as a *Match Accept*. Without this stage Agent 1 would have to send the transaction to the controller at the propose stage. As the propose stage has a high probability of leading to breakdown in negotiations this would constrain the agent too much. Any transaction submitted to the controller must be considered in the forward looking state of the agent.

3.4.3 Baseline Agent with world model

The baseline agent with world model uses information gained from acceptances and declines of the proposals she makes to create a price model for each good. It then uses the price model to offer the price which assumes the highest likelihood of trade.

Figure 2: A sequence diagram of a successful negotiation ending with settlement of the transaction via the controller.



Agent 1
Controller
Agent 2
CFP(msg_id=1, target=0, dialogue_id=1, query=Query)
Propose(msg_id=2, target=1, dialogue_id=1, proposals=Proposals)
Accept(msg_id=3, target=2, dialogue_id=1)
Message(msg_id=4, target=2, dialogue_id=1, transaction=Transaction)
Accept(msg_id=4, target=3, dialogue_id=1)
Message(msg_id=5, target=2, dialogue_id=1, transaction=Transaction)

3.5 Strategies

The focus of a rational agent will be to discover how they can arrive at an optimal bundle - as defined by their preferences - through successive trades. In the current specification, emphasis for agents is placed on a) finding the right agents to trade with, and b) doing the right trade with them. This might involve identifying other agents' needs to arrive at the optimal trading sequence. However, a dummy agent which simply selects random bargaining partners and trades if it is beneficial would still be somewhat competitive. It would then be up to the developer

Figure 3: A sequence diagram of a negotiation which breaks down on the Propose because *a*1 does not deem the proposal beneficial.

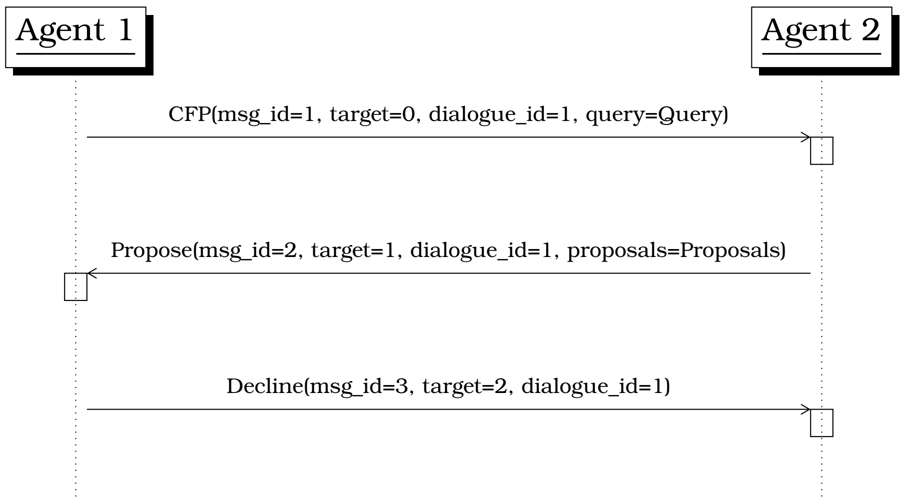
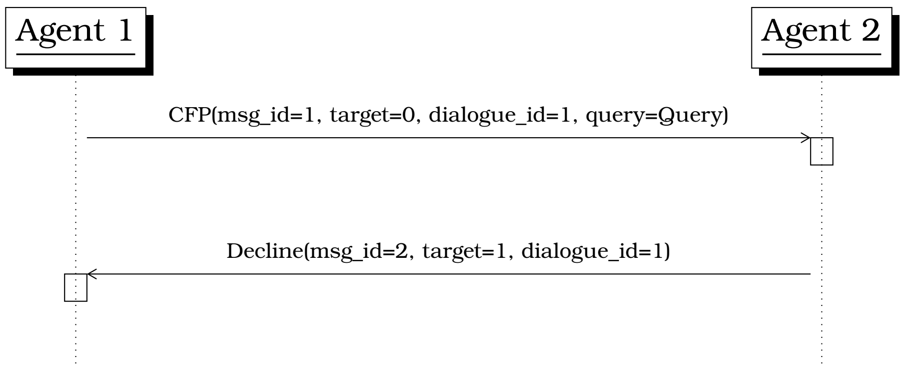

Agent 1
Agent 2
CFP(msg_id=1, target=0, dialogue_id=1, query=Query)
Propose(msg_id=2, target=1, dialogue_id=1, proposals=Proposals)
Decline(msg_id=3, target=2, dialogue_id=1)

Figure 4: A sequence diagram of a negotiation which breaks down on the CFP because *a*2 does not have anything to propose based on the CFP query.


Agent 1
Agent 2
CFP(msg_id=1, target=0, dialogue_id=1, query=Query)
Decline(msg_id=2, target=1, dialogue_id=1)

to focus exclusively on more simple message passing or extend the scope to include implementing elaborate discovery strategies (which utilise the OEF fully for agent discovery), opponent modelling, (multi-party) trading strategies and even implement an agent who runs an auction. Crucially, we are not restricting complexity in agent development in this setup, what we do is provide a point of coordination (i.e. focus on simple bilateral good exchange) for agent developers.

With this use-case we offer low barriers to entry and avoid a scenario where only experts in AI or MAS can participate in the competition. Traditionally, multi-agent system competitions targeted experienced teams of multi-agent developers. This has academic and technological benefits, e.g. it pushes the field forward. However it excludes casual developers from competing. Traditional competitions have a strong focus on optimal agent strategies and due to the environments agents are exposed to, this requires knowledge in advance optimisation techniques. Fetch wants to deliver a competition where optimisation techniques are not strictly required for an agent to be able to compete.

The selected use-case is the most basic trading setup we could think of which still has a competitive element. Should it transpire that the setup is too simplistic (i.e. degenerate) then we can extend it.

3.6 Controller GUI

We provide a GUI for competition organisers to monitor the competition in real time and to help with analysing historic competition data.

3.7 Agent GUI

We provide a GUI for agent developers to monitor their agent in real time and to help with analysing historic agent behaviour.

3.8 Empirical Analysis

Research metrics to determine if the competition is interesting, e.g. a good enough number of agents (i.e. min_agents) will have to be determined in internal tests for the competition to be worthwhile.

4 Developer Community

4.1 Communication

A dedicated communication channel is opened for agent developers to exchange ideas and communicate with Fetch.ai developers. More details could be found in www.fetch.ai.

4.2 Code Sharing

Developers who enter the competition will likely want to improve their agent development. For this reason - and in the spirit of openness - we may incentivise participants to share their agent code. However, it has been decided that no participant is forced to share their code in order to participate.

5 Closing Remarks

5.1 Rules

The following regulations are enforced in the competition:

- Any action that goes against the spirit of the competition is strongly discouraged. Examples of such behaviour includes, but is not limited to:

  - Launching any form of attack on any of the components of the competition, such as the OEF, other agents, the competition manager agent.
  - Participants' collusion with one another, through sacrificing one agent's score to increase another agent's score.

- Only one agent is allowed per individual/team.
- Every individual/team wishing to participate in the competition has to go through a KYC procedure. The details of this is provided in www.fetch.ai.
- Participants are required to only use the OEF for agent-to-agent communication, and cannot use another medium for that.
- Agents can in principle communicate peer to peer. This is a realistic expectation which is difficult to enforce against.

5.2 Future TACs

There are many ways the trading environment could be made richer, and the domain more complex. A natural extension is to introduce a market through a centralised auction process. Theoretically, this should cause the agent-to-agent negotiation to unravel (for more information, please see here). However, it would be interesting to observe what happens in a multi-agent world where agents are unlikely (programmed to be) hyper-rational.

Below we list a number of features which can enrich a competition:

- **Decisions under uncertainty**: agents face uncertainty. For example, a partner in trade's preferences, accurate current good holdings, and its various strategies (e.g. pricing, opponent modelling, search and discovery, etc) are not publicly accessible information. Thus, any attempts to take advantage of those information would requiring some approximation technique.

- Agents to be required to deploy strategies based on a variety of techniques (e.g. RL, other ML techniques, Evolutionary/genetic algorithms, logic-based, etc).
- **Multiplicity of issues**: so several agent skills are needed and no single type of agent strategy is superior in all markets.
- Explore extremes of purely strategic (two players) and purely aggregate (price taking e.g. in a perfectly competitive market whether I buy or not has zero impact on the price by definition).

When developing competitions we aim to avoid arbitrary elements which do not mirror. For example, involving a combinatorial auction in a setting where there is no evidence of such an auction being conducted in that market in reality.