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EH2750 Computer Applications in Power Systems, Advanced Course.

Lecture 8

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Acknowledgement

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  Professor Rosenschein of the Hebrew University Jerusalem, Israel

  and

  Dr. Georg Groh, TU-München, Germany.

- Available at the Student companion site of the Introduction to Multi Agent Systems book

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Outline of the Lecture

- Repeating where we are right now
  - Intelligent Agents of various types
  - How to make agents think and plan
- Multi-agent interactions
  - Some concepts for cooperation
- Allocating Scarce Resources - Auctions

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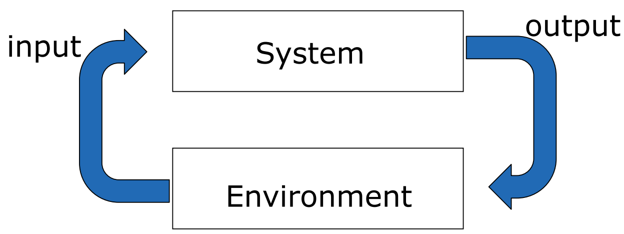
What is an Intelligent Agent?

- The main point about agents is they are *autonomous*: capable of acting independently, exhibiting control over their internal state
- Thus: *an intelligent agent is a computer system capable of flexible autonomous action in some environment in order to meet its design objectives*

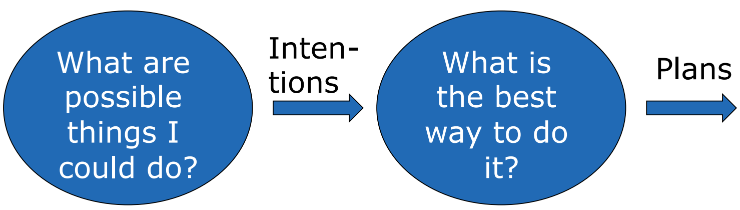


The discussion so far

- Chapter 2 describes the idea of agents that perform tasks in an environment and sets some definitions
- Chapters 3, 4, & 5 describe three different approaches to describing and developing the apparent Intelligence in the agents.
  - Chapter 3 – Deductive Reasoning Agents
  - Chapter 4 – Practical Reasoning Agents
  - Chapter 5 - Reactive (and Hybrid Agents)
- In the Excerpt from the AI book used in Lecture #4 we took a look at planning and searching
- Today we start looking at the <u>Multi</u> in Multi-agent systems

Practical Reasoning

- Human practical reasoning consists of two activities:
  - *deliberation*
    deciding *what* state of affairs we want to achieve
  - *means-ends reasoning*
    deciding *how* to achieve these states of affairs
- The outputs of deliberation are *intentions*

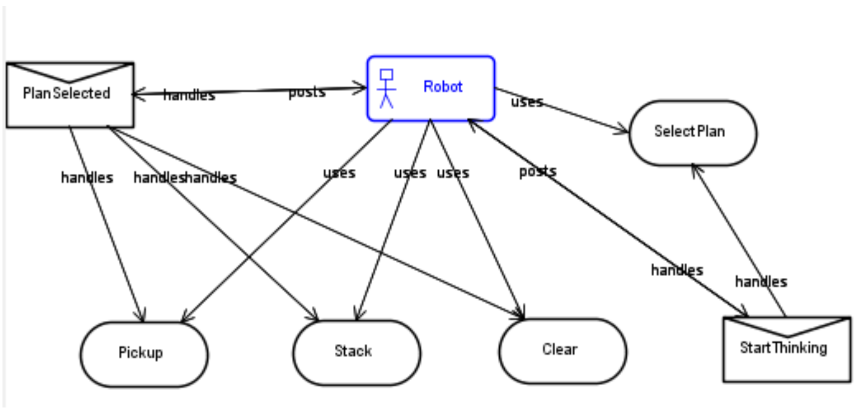


Practical Reasoning Agent

```
function SIMPLE-PROBLEM-SOLVING-AGENT(percept) returns an action
  inputs: percept, a percept
  static: seq, an action sequence, initially empty
          state, some description of the current world state
          goal, a goal, initially null
          problem, a problem formulation

  state ← UPDATE-STATE(state, percept)
  if seq is empty then do
     goal ← FORMULATE-GOAL(state)
     problem ← FORMULATE-PROBLEM(state, goal)
     seq ← SEARCH(problem)
  action ← FIRST(seq)
  seq ← REST(seq)
  return action
```

How this can look in JACK



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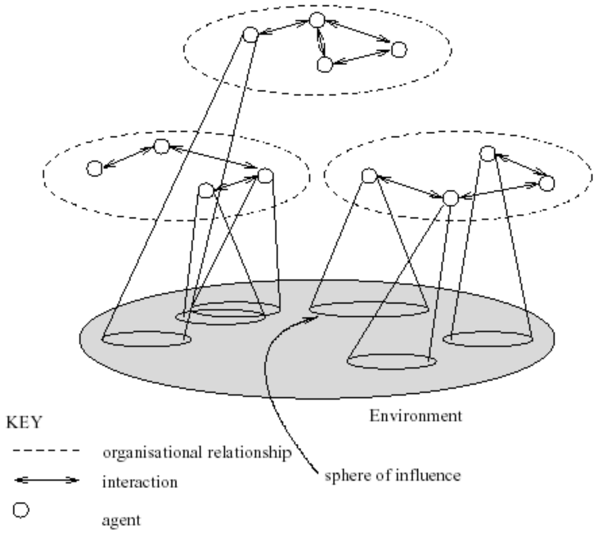
Multi-agent Systems



Multi-agent Systems

Contains a number of agents…

- …which interact through communication…
- …are able to act in an environment…
- …have different "spheres of influence" (which may coincide)…
- …will be linked by other (organizational) relationships

Working Together

- Why and how do agents work together?

- Important to make a distinction between:
  - *benevolent agents*
  - *self-interested agents*

Benevolent Agents

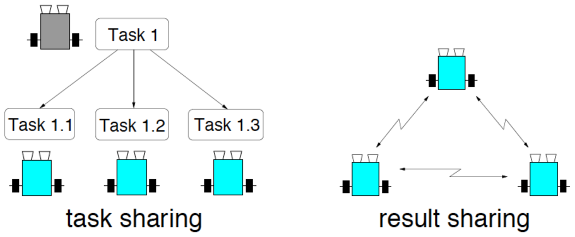
- If we "own" the whole system, we can design agents to help each other whenever asked
- In this case, we can assume agents are *benevolent*: our best interest is their best interest
- Problem-solving in benevolent systems is *cooperative distributed problem solving* (CDPS)
- *Benevolence simplifies the system design task enormously!*

Self-Interested Agents

- If agents represent individuals or organizations, (the more general case), then we cannot make the benevolence assumption
- Agents will be assumed to act to further their own interests, possibly at expense of others
- Potential for *conflict*
- May complicate the design task enormously

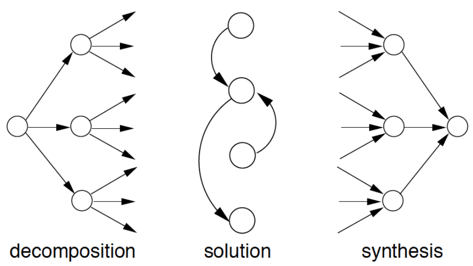
Benevolent Agents
Task Sharing and Result Sharing

- Two main modes of cooperative problem solving:
  - *task sharing*:
    components of a task are distributed to component agents
  - *result sharing*:
    information (partial results, etc.) is distributed



Benevolent Agents
Cooperative Distributed Problem Solving

- CDPS is concerned with investigation of:
  - Problem subdivision
  - Sub-Problem distribution
  - Result synthesis
  - Optimization of problem solver coherence
  - Optimization of problem solver coordination



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Benevolent Agents

Coherence

Coherence: Refers to "how well the MAS behaves as a unit along some dimension of evaluation". Coherence may be measured in terms of

- Solution quality
- resource usage
- conceptual clarity of operation
- performance degradation if unexpected failure occurs

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Benevolent Agents

Coordination

- ***Coordination:*** "The degree...to which [the agents] can avoid 'extraneous' activity [such as] ...synchronizing and aligning their activities"

→ Poor coordination if

- Agents clobber each other's sub-goals
- Lots of communication (no mutual predictability (e.g. by expressive models of each other))
- Destructive interference if conflict

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Self-Interested Agents

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Utilities and Preferences

- Assume we have just two agents: $Ag = \{i, j\}$
- Agents are assumed to be *self-interested*: they *have preferences over how the environment is*
- Assume $\Omega = \{\omega_1, \omega_2, \ldots\}$ is the set of "outcomes" that agents have preferences over
- We capture preferences by *utility functions*:

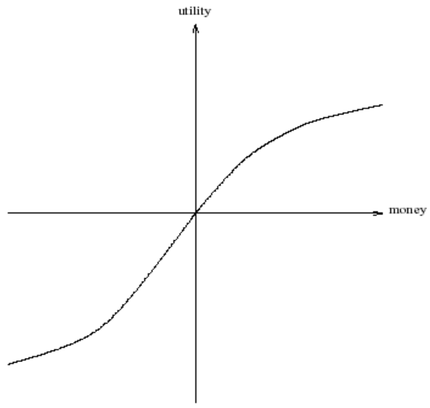
$$u_i = \Omega \to \mathbf{R}$$
$$u_j = \Omega \to \mathbf{R}$$

- Utility functions lead to *preference orderings* over outcomes:

$$\omega \succeq_i \omega' \text{ means } u_i(\omega) \geq u_i(\omega')$$
$$\omega \succ_i \omega' \text{ means } u_i(\omega) > u_i(\omega')$$

What is Utility?

- Utility is *not* money (but it is a useful analogy)
- Typical relationship between utility & money:



Multiagent Encounters

- We need a model of the environment in which these agents will act…
  - agents simultaneously choose an action to perform, and as a result of the actions they select, an outcome in Ω will result
  - the *actual* outcome depends on the *combination* of actions
  - assume each agent has just two possible actions that it can perform, *C* ("cooperate") and *D* ("defect")
- Environment behavior given by *state transformer function*:

$$\tau : \underbrace{Ac}_{\text{agent } i\text{'s action}} \times \underbrace{Ac}_{\text{agent } j\text{'s action}} \to \Omega$$

Multiagent Encounters

- Here is a state transformer function:

$$\tau(D,D)=\omega_1 \quad \tau(D,C)=\omega_2 \quad \tau(C,D)=\omega_3 \quad \tau(C,C)=\omega_4$$

(This environment is sensitive to actions of both agents.)

- Here is another:

$$\tau(D,D)=\omega_1 \quad \tau(D,C)=\omega_1 \quad \tau(C,D)=\omega_1 \quad \tau(C,C)=\omega_1$$

(Neither agent has any influence in this environment.)

- And here is another:

$$\tau(D,D)=\omega_1 \quad \tau(D,C)=\omega_2 \quad \tau(C,D)=\omega_1 \quad \tau(C,C)=\omega_2$$

(This environment is controlled by *j*.)

Rational Action

- Suppose we have the case where *both* agents can influence the outcome, and they have utility functions as follows:

$$u_i(\omega_1)=1 \quad u_i(\omega_2)=1 \quad u_i(\omega_3)=4 \quad u_i(\omega_4)=4$$
$$u_j(\omega_1)=1 \quad u_j(\omega_2)=4 \quad u_j(\omega_3)=1 \quad u_j(\omega_4)=4$$

- With a bit of abuse of notation:

$$u_i(D,D)=1 \quad u_i(D,C)=1 \quad u_i(C,D)=4 \quad u_i(C,C)=4$$
$$u_j(D,D)=1 \quad u_j(D,C)=4 \quad u_j(C,D)=1 \quad u_j(C,C)=4$$

- Then agent i' s preferences are:

$$C,C \succeq_i C,D \quad \succ_i \quad D,C \succeq_i D,D$$

- "*C*" is the *rational choice* for i.
  (Because i prefers all outcomes that arise through *C* over all outcomes that arise through *D*.)

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Payoff Matrices

- We can characterize the previous scenario in a *payoff matrix*:

		i	
		defect	coop
j	defect	1 1	4 1
	coop	1 4	4 4

- Agent i is the *column player*
- Agent j is the *row player*

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Dominant Strategies

- Given any particular strategy (either *C* or *D*) of agent i, there will be a number of possible outcomes
- We say s_1 *dominates* s_2 if every outcome possible by i playing s_1 is preferred over every outcome possible by i playing s_2
- A rational agent will never play a dominated strategy
- So in deciding what to do, we can *delete dominated strategies*
- Unfortunately, there isn't always a unique undominated strategy

Nash Equilibrium

- In general, we will say that two strategies s_1 *and* s_2 are in Nash equilibrium if:
  1. under the assumption that agent i plays s_1, agent j can do no better than play s_2; and
  2. under the assumption that agent j plays s_2, agent i can do no better than play s_1.
- *Neither agent has any incentive to deviate from a Nash equilibrium*
- Unfortunately:
  1. *Not every interaction scenario has a Nash equilibrium*
  2. *Some interaction scenarios have more than one Nash equilibrium*

Competitive and Zero-Sum Interactions

- Where preferences of agents are diametrically opposed we have *strictly competitive* scenarios
- Zero-sum encounters are those where utilities sum to zero:

  $u_i(\omega) + u_j(\omega) = 0$ for all ω in Ω
- Zero sum implies strictly competitive
- Zero sum encounters in real life are very rare … but people tend to act in many scenarios as if they were zero sum

The Prisoner's Dilemma

- Two men are collectively charged with a crime and held in separate cells, with no way of meeting or communicating. They are told that:
  - if one confesses and the other does not, the confessor will be freed, and the other will be jailed for three years
  - if both confess, then each will be jailed for two years
- Both prisoners know that if neither confesses, then they will each be jailed for one year

The Prisoner's Dilemma

- Payoff matrix for prisoner's dilemma:

		i defect	*i* coop
j	defect	2 (i), 2 (j)	1 (i), 4 (j)
j	coop	4 (i), 1 (j)	3 (i), 3 (j)

- Top left: If both defect, then both get punishment for mutual defection
- Top right: If i cooperates and j defects, i gets sucker's payoff of 1, while j gets 4
- Bottom left: If j cooperates and i defects, j gets sucker's payoff of 1, while i gets 4
- Bottom right: Reward for mutual cooperation

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The Prisoner's Dilemma

- The *individual rational* action is *defect*
  This guarantees a payoff of no worse than 2, whereas cooperating guarantees a payoff of at most 1
- So defection is the best response to all possible strategies: both agents defect, and get payoff = 2
- But *intuition* says this is *not* the best outcome:
  Surely they should both cooperate and each get payoff of 3!

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The Prisoner's Dilemma

- This apparent paradox is *the fundamental problem of multi-agent interactions*.
  It appears to imply that *cooperation will not occur in societies of self-interested agents*.
- Real world examples:
  - nuclear arms reduction ("why don't I keep mine. . . ")
  - free rider systems — public transport;
- The prisoner's dilemma is *present everywhere*.
- Can we recover cooperation?
  - Well, yes we can introduce auctions, negotiations and argumentation. More on this next lecture!

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Allocating Scarce Resources

- Allocation of scarce resources amongst a number of agents is central to multiagent systems.
- Resource might be:
  - a physical object
  - the right to use land
  - computational resources (processor, memory, . . .)
  - Network capacity
  - Amount of energy
  - ….

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Reaching Agreements

- The extreme case of a Multiagent encounter is the zero-sum. (*Profit only at expense of others*)
- Normal case is the "Win-win-situation" where mutually beneficial agreement is possible
- Reaching Agreements is fundamental for social intelligence and society building in general
- Reaching Agreements is a result of Negotiation, Auctions and/or Argumentation
- How do you construct algorithms these types of interactions

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Algorithm Design Criteria

- We want to have a design of the algorithm that has certain properties:

1. Guaranteed success - Agreement is certain
2. Maximizing social welfare - Agreement maximizes sum of utilities of all participating agents
3. Computationally efficient

Algorithm Design Criteria, continued

4. Pareto efficiency: iff there exists no other agreement which increases utility of at least one agent while not decreasing the utility of the other agents
5. Individual Rationality: Following protocol is in best interest of all agents (no incentive to cheat, deviate from protocol etc.)
6. Stability: Protocol gives agents incentive to behave in a certain way. (→ e.g. by establishing Nash-Eq.)
7. Simplicity: Protocol makes for the agent appropriate strategy „obvious‟. (Agent can tractably determine optimal strategy)
8. Distribution: no single point of failure; minimize communication

What are auctions?

- Concerned with traders and their allocations of:
  - Units of an indivisible good; and
  - Money, which is divisible.
- Assuming some initial allocation
- Exchange is the free alteration of allocations of goods and money between traders

Auctions

- Auctions are simple → easy to implement
- Auction =consists of (Auctioneer, Bidders, Good);
  Goal of the Auctioneer is to maximize price for good;
  Goal of the Bidders is to minimize price for good;
  Each bidder has personal price maximum
- Auctioneer: Tries to reach goal by choosing appropriate auction mechanism
- Bidders: Try to reach goal by choosing appropriate strategy
- Auction algorithms differ by:
  - Winner determination,
  - Secrecy of bids,
  - Auction procedure

Single vs. Multi-dimensional auctions

- Single dimensional auctions
  - The only content of an offer are the price an quantity of some specific type of good.
  - "I'll bid $200 for those 2 chairs"
- Multi dimensional auctions
  - Offers can relate to many different aspects of many different goods.
  - "I'm prepared to pay $300 for those two red chairs, but $300 if you can deliver them tomorrow."

Value of the goods

Good has a public (common) value: Good has the same value for all bidders. (E.g.: One-Dollar-Bill)

Good has private value: Good has different value for each agent. (E.g.:)

Good has correlated value: Value of good depends on own private value and private value for other agents. (E.g.: Buy sth. with intention to sell it later)

Winner Determination

- First price: Highest bid wins, Winner pays his bid
- Second price: Highest bid wins. Winner pays second-highest bid
- General case, highest bid wins, pays n-k bid.

Secrecy of the Bids

- Open cry: All agent's know all agent's bids.
- Sealed bid: No agent knows other agent's bids

Auction Procedure

- One shot: Only one bidding round
- Ascending
  - Auctioneer begins at minimum price, bidders increase bids
  - Also known as English Auction
- Descending
  - Auctioneer begins at price over value of good and lowers the price at each round
  - Also known as Dutch auction

English Auctions

- Most common form (human world)
- **Open cry, first price, ascending**.
- Dominant strategy: Bid slightly more than current bit, withdraw if bid reaches personal valuation of good
- If uncertainty of (private or public) value of good exists:
  - "Should you be happy that you won the good?"
  - "Why did the other bidders not bid more?"
- Possibly: Although winning bid is below personal valuation of winner, the "true value" may be less than bid → "Winner's curse". (E.g. bidding for gold-mine)

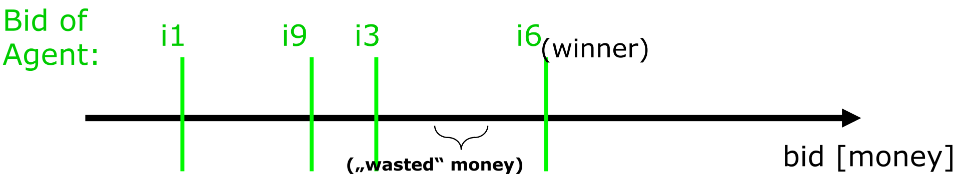
Dutch Auctions

- **Open cry, first-price, descending**.
- No dominant strategy. Winner's curse also possible.

Sealed-bid First-price One-shot

- "Pseudo"-dominant strategy: (Assuming that others bid their true valuation): Bid less than true valuation.

How much less → ??

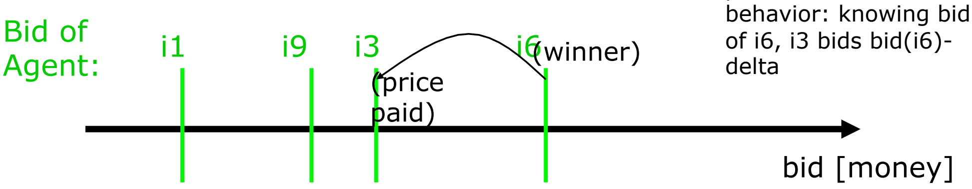


Vickrey Auctions

- **Sealed-bid, second-price, one shot**
- Dominant strategy: (Assuming that others bid their true valuation): Bid true valuation.

Why? If you bid less than your true valuation → you only decrease your chances, but you will not influence the price you have to pay.
(As in all auctions: If you bid more than your true valuation → you risk winner's curse)

possible antisocial behavior: knowing bid of i6, i3 bids bid(i6)-delta



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Combinatorial Auctions

- Until now, we have considered auctions for one indivisible good.
- Now consider auctions for goods that are divisible
- Like for instance
  - Amount of available energy next hour, or
  - Power that can flow along a line

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Formulation

$$\mathcal{Z} = \{z_1, \ldots, z_m\}$$

is a set of items to be auctioned, we have the usual set of agents

$$Ag = \{1, \ldots, n\},$$

and we capture preferences of agent i with the valuation function:

$$v_i : 2^{\mathcal{Z}} \mapsto \mathbb{R}$$

meaning that for every possible bundle of goods

$$Z \subseteq \mathcal{Z}, v_i(Z)$$

says how much Z is worth to Agent i.

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Some additional facts & assumptions

If

$$v_i(\emptyset) = 0$$

then we say that the valuation function for i is normalised. Meaning that if an agent is allocated nothing it is worth nothing.

Similarly, we have that

$$Z_1 \subseteq Z_2 \text{ implies } v_i(Z_1) \leq v_i(Z_2)$$

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Winner (or allocation) determination

- An allocation is a list of sets (allocations) $Z_1 \ldots Z_n$ for each agent Ag_i so that

$$Z_i \subseteq \mathcal{Z}$$

- And for all i,j in Ag such that $i \neq j$ we have $Z_i \wedge Z_j = 0$
- Valid for discrete sets of goods
- A general continuous case is similarly constrained by the sum of $Z_1 \ldots Z_n \leq Z$

How to do the allocation then?

- A reasonable assumption is to allocate in a way that maximises the social welfare, i.e. Maximizing the toal value achieved, the sum of all utilities.

$$sw(Z_1, \ldots, Z_n, v_1, \ldots, v_n) = \sum_{i=1}^{n} v_i(Z_i)$$

Cobinatorial Auction setup

- Given this, we can define a *combinatorial auction*.
- Given a set of goods $\mathcal{Z}$ and a collection of valuation functions $v_1, \ldots, v_n$, one for each agent $i \in Ag$, the goal is to find an allocation

$$Z_1^*, \ldots, Z_n^*$$

that maximizes sw, in other words

$$Z_1^*, \ldots, Z_n^* = \arg \max_{(Z_1, \ldots, Z_n) \in alloc(\mathcal{Z}, Ag)} sw(Z_1, \ldots, Z_n, v_1, \ldots, v_n)$$

- Figuring this out is *winner determination*.

Determining the allocation

- How do we do this?
- Well, we could get every agent i to declare their valuation $\hat{v}_i$
  - The hat denotes that this is what the agent *says*, not what it necessarily is.
  - The agent may lie!
- Then we just look at all the possible allocations and figure out what the best one is.

Computational efficiency?

- One problem here is *representation*, valuations are exponential:

$$v_i : 2^{\mathcal{Z}} \mapsto \mathbb{R}$$

  - A naive representation is impractical.
  - In a bandwidth auction with 1122 licenses we would have to specify 2^{1122} values for each bidder.
- Searching through them is computationally intractable.

So, how do we do it then?

- Searching through all combinations is a basic problem but intractable due to computation resources needed.
- However,his is the worst case result, so it may be possible to
- We can try to develop approaches that are optimal and run well in many cases.
- Can also forget optimality and either:
  - use heuristics; or
  - look for approximation algorithms.
- Common approach: code the problem as an integer linear program and use a standard solver – often works in practice.
- In practice a constraint satisfaction problem, that can be solved with different search mechanisms

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