From its simple beginnings in the town square, the “marketplace” has grown to encompass the entire global business environment. The vast and intricately woven infrastructure necessary for this level of commerce involves issues of money, credit, insurance, legal infrastructure, corporate and individual identities, and fraud detection and deterrence. As market activities move online, we have an opportunity to re-examine the processes and conventions that governed pre-Internet commerce, and to restructure those that need it for the virtual marketplace.

One concept being challenged by new technologies is fixed pricing, which became prevalent in western society during the industrial revolution when mass production and widespread delivery of goods made price negotiation impractical. A Wyoming frontiersman could not negotiate with Sears, Roebuck and Co. about the mail-order catalog price of a pair of boots in the late 1890s. The Internet now has the potential to reverse that trend.

**Dynamic Pricing**

*Dynamic pricing* systems, already in wide use for items such as securities, airline tickets, and oil, determine the price of an item by the participants’ expression of supply and demand. Because prices fluctuate continually in these systems, you must aggregate supply and demand in the marketplace to effectively establish a price for a product or service. *Auctions* are the standard means of performing this aggregation. They establish prices based on participants’ bids for buying or selling commodities. An auction is a disinterested mediator that simply follows a formal policy that defines its behavior as a function of the bids it receives.

Not long ago, “auction” meant the classic English outcry auction with its fast-talking, formally dressed auctioneer and crowded room of bidders, but these days the word is more likely to bring to mind a Web site such as eBay. The basic structure is similar—buyers keep outbidding each other until the auction closes—but the rules differ subtly. In particular, the classic English auction ends when no further bids are tendered during the period it takes the auctioneer to say, “going once, going twice...sold!” and eBay’s version ends at a fixed time.
A more precise way to describe an auction is to be explicit about the rules that determine its behavior. My colleagues and I formalized a set of rules that describe an auction’s policies around three basic tasks:

- receiving bids,
- revealing intermediate information, and
- clearing the auction.

These tasks can be interleaved and repeated.

In the following discussion, I illustrate some parameter values by referencing named auctions, which are defined in Table 1 (next page). I assume that each participant has only one bid in the auction, but because the parameterization scheme allows arbitrarily complex bids, the assumption is not restrictive.

Before defining the parameters, I will introduce some general properties.

- **Auction scope** refers to the number of distinct types of commodities being traded. The scope is one in most familiar cases, but can be much greater in multicommodity auctions.
- **Nature of goods.** Each type of good can be discrete or continuous, but most auction research studies the allocation of discrete goods.

Elsewhere, we have provided precise definitions and mathematical notation for these properties and all the following auction rules. We attempt to define the parameters to be orthogonal to one another and inclusive of the many existing auction types.

**Auction Rules**

Bidding rules determine what actions participants can take—particularly, the conditions under which they can introduce, modify, or withdraw bids. This determination could depend on the bidder’s identity, the auction’s state, or the bid history. The bidding rules summarized in Table 2 (next page) constrain bids in several ways.

The bid-dominance and beat-the-quote rules are used to ensure that auctions progress toward a quiescent state. In an English outcry auction, the beat-the-quote rule is sufficient to create ascending prices, but more complex mechanisms like combinatorial auctions (see the “Advanced Auctions” section) achieve the desired ascending (or descending) behavior using both rules.

Clearing is the task of determining prices, quantities, and trading partners as a function of the bids. Table 3 (page 39) summarizes the parameters that govern clearing.

As they progress, many auctions reveal information on their current state to the participants. After every bid, for example, the continuous double auction (CDA) posts the new bid-and-ask spread. When a new bid is received in the English outcry auction, the auctioneer calls out the new price that participants must offer in order to become the tentative winner. Auctions in which no intermediate information is revealed, like the procurement auction, are typically called “sealed-bid” auctions.

The rules defined in Table 4 (page 39) control the type and frequency of information revealed.

**Implications**

The parameterization described above highlights three important issues. First, because these auction parameters are orthogonal to a great extent, there are millions of permutations, and only a few have been analyzed in the literature. Not all of the options will result...
in useful auctions, but as yet unstudied, design will very likely have practical applications. For example, eBay's English auction varies in important ways from any studied in the literature. Although the rules induce a bidding strategy equivalent to a first-price, sealed-bid auction, the extended period before the end of the auction attracts potential bidders.

Second, the parameterization suggests a modular approach to auction server design, which we have implemented in the Michigan Internet AuctionBot.2 Our experience indicates that the matching function is the key architectural component. We can design and implement this function independently of all other parameters, and then achieve particular subclasses by setting the other parameters appropriately.

Third, the parameterization defines a concise, flexible semantics for developing an XML-based auction description language, and the mathematical foundations specify the precise meaning of the particular parameters. A formal language enables us to communicate the auction rules to other software components. This is particularly necessary for developing flexible bidding agents.

Table 1. Named Auctions

<table>
<thead>
<tr>
<th>Auction type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>English outcry</td>
<td>This is the classic single-item auction in which the auctioneer calls out a price and a buyer signals willingness to bid at the cried price. The object is sold to the highest bidder when no further signals are received within a specified time period.</td>
</tr>
<tr>
<td>Procurement</td>
<td>A single buyer wants to purchase a good or service. The auction is typically done with sealed bids, and the seller with the lowest bid wins the right to sell the item at the price of her bid.</td>
</tr>
<tr>
<td>Continuous double</td>
<td>The CDA is an abstraction of the stock market. Any participant can place a buy or sell offer, and the auction checks every new bid against the standing bids to see if a match is possible. If so, the transaction is recorded and only the unmatched portion of the bid remains.</td>
</tr>
</tbody>
</table>

Table 2. Bidding Rules

<table>
<thead>
<tr>
<th>Rule</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed rules</td>
<td></td>
</tr>
<tr>
<td>Bidding language</td>
<td>The bidding language determines the types of offers that bidders can express. The only semantic element in the English auction's bidding language is price; the quantity is always a single unit. Multi-unit auctions might allow bids for multiple units at a single price, or at multiple prices. A combinatorial auction for discrete goods might permit offers for bundles, and an auction for an arbitrarily divisible commodity might permit bids that are mathematical correspondences between quantities and prices.</td>
</tr>
<tr>
<td>Bid divisibility</td>
<td>Some multi-unit auctions require that bids can be partially filled, while others permit participants to place all-or-nothing bids. When bids cannot be split, finding the revenue-maximizing combination of bids is a set-packing problem. Many online auctions use a greedy algorithm for selecting the winning bids rather than computing the optimal combination of bids.</td>
</tr>
<tr>
<td>Buyers and sellers</td>
<td>The classic auctions all have a single seller (the bidder with the singular right to place a sell bid) and multiple buyers. Procurement auctions are the inverse—a single buyer decides among multiple sellers. The stock market, on the other hand, allows all participants to play either role. For most purposes, sellers and buyers are completely symmetric. In our work, for example, we treat a sell offer as a bid with negative quantity.</td>
</tr>
</tbody>
</table>

Context-dependent restrictions

<table>
<thead>
<tr>
<th>Rule</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beat-the-quote</td>
<td>The English auction requires that a new bid “beat” the current highest bid, but this definition does not extend well into the multicommodity space. We have proposed a more versatile definition based on the intuition that by beating the quote an agent becomes more active—buying or selling more objects—than with its previous bid.</td>
</tr>
<tr>
<td>Bid dominance</td>
<td>This rule requires a bidder’s replacement offer to be a well-defined improvement over the previous bid. Unlike the beat-the-quote rule, it is defined with respect to the bidder’s current offer, rather than the auction’s price quote. Dominance can be either ascending (typical for buy offers) or descending (typical for sell offers).</td>
</tr>
<tr>
<td>Withdrawal and expiration</td>
<td>Some auctions, like the CDA, permit agents to withdraw bids or submit them with predefined expiration times. Others, like the English, do not permit either action. In some combinatorial auctions, a bidder can withdraw an offer only if it is not currently winning.</td>
</tr>
<tr>
<td>Activity rules</td>
<td>Activity rules are a recent innovation designed to promote bidding activity. In complex auctions, there is an incentive to hold back bids and attempt to free ride on others’ bids. Activity rules define a participant’s allowable actions in one round as a function of the participant’s actions in the previous round(s).</td>
</tr>
</tbody>
</table>
Choosing an Auction Type

Given that we can use this framework to describe millions of different auction types, choosing one becomes extremely complex. Economists have defined a set of properties that can assist us in the quest.

Designers want an auction to generate socially efficient allocations. The auction should also reach an equilibrium, that is, a state from which no participant wishes to deviate. An auction is individually rational if it does not make any participant worse off than when it started. In incentive-compatible auctions, participants maximize their utility by truthfully stating their preferences (by bidding their true value). Incentive compatibility is desirable because agents need not spend any effort modeling the other participants. When a bidder’s actions depend on its (usually probabilistic) model of the other bidders, it occasionally places bids that result in inefficient outcomes.

In economics, you construct a model of the market under consideration and then determine the most likely bidding strategies. Given the information available to the participants, an equilibrium strategy provides the highest expected utility. When an agent has complete and recursive knowledge of the other agents’ utility functions, the equilibrium is the Nash equilibrium of game theory.

Two major classes of models exist. In the independent private values model, each participant independently values the goods. Learning that participant B values the good at y does not change participant A’s value for it. This may be an appropriate model of a corporation determining the value of inputs to its manufacturing process. The affiliated common values model assumes that the object has some true value, and that participants have possibly incorrect beliefs about it. For example, when bidding on oil-drilling rights, each company sur-

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Table 3. Clearing Rules

<table>
<thead>
<tr>
<th>Rule</th>
<th>Definition</th>
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</thead>
<tbody>
<tr>
<td>Clear timing</td>
<td>This rule defines the timing and triggering action for a clear. In an English auction, the clear is inactivity-based, triggered by the expiration of a period in which no new bids are received. In a CDA, clears are (apparently) continuous. Clears might also be initiated by a fixed schedule or by a random event, perhaps to discourage particular strategic behaviors. An auction can combine these triggering events in various ways. For instance, Amazon.com’s version of the English auction clears at the latest of a fixed time and a period of inactivity.</td>
</tr>
<tr>
<td>Closing conditions</td>
<td>The English auction closes on the same condition that it clears—i.e., inactivity. More generally, closing conditions are separate from clearing. For example, the stock market clears whenever there is bidding activity and closes at the end of the day. An auction can close at a scheduled time, a random time, after a period of inactivity, or when the bid of the designated agent (for instance the seller, in a single-seller auction) is matched.</td>
</tr>
<tr>
<td>Matching function</td>
<td>When a clear occurs, the auction runs an algorithm that implements its matching policy to determine who sells to whom and at what price. We further decompose the matching function into a policy for winner determination (with tie-breaking provisions), and a policy that sets prices (see the sidebar, “Matching Functions”).</td>
</tr>
<tr>
<td>Fees</td>
<td>Money might also flow to (or from) the auctioneer in the form of fees. Typical fee structures include an entrance fee, a fee per bid placed (for example, a listing fee), or a charge that is proportional to the payment between the buyer and seller. The auction might charge fees to the buyer, the seller, or both.</td>
</tr>
</tbody>
</table>

Table 4. Information Revelation Rules

<table>
<thead>
<tr>
<th>Rule</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price quote</td>
<td>The price quote, computed from current bids by a quote function, informs participants of the hypothetical result had the auction cleared at the time the quote was issued. Separating quotes convey enough information for each agent to exactly compute its tentative allocation. Nonseparating quote functions have been suggested for complex situations in which calculating the separating quote is computationally expensive.</td>
</tr>
<tr>
<td>Quote timing</td>
<td>This parameter specifies the events that trigger the system to compute and announce a price quote. The values appropriate for specifying the timing of clears are also appropriate for quotes.</td>
</tr>
<tr>
<td>Order book</td>
<td>This term is commonly used in organized exchanges to refer to the current set of active bids. The auctioneer might keep the book closed, reveal only the current winning bids, or reveal all entries. Online sites like eBay and Amazon reveal the current winning bids.</td>
</tr>
<tr>
<td>Transaction history</td>
<td>When clears and quotes are not coincident, only the bidders participating in the exchange know the transaction price. This parameter allows the auction designer to reveal the transaction price to the entire bidding population.</td>
</tr>
</tbody>
</table>
veys the drilling site and estimates the number of barrels of oil present. Because there is a fixed amount of oil in the reserve and the right to drill in the field has the same value to each bidder, learning bidder B’s estimate of the value of the drilling rights should prompt A to update its estimate.

There are three well-known and somewhat surprising results from auction theory that should be mentioned here. The first is known as the revenue equivalence theorem. It demonstrates that when a single seller offers a single item, and the buyers have independent private values, all of the classic single-item auctions (English, Dutch, first-price sealed-bid, and second-price sealed-bid) generate the same revenue to the seller. In experimental investigations, however, the English auction often generates more revenue. The reasons for this might be more psychological than decision-theoretical: Participants bid higher in English auctions because they enjoy the competitive nature of the auction. This aspect of human nature might contribute to the popularity of variants of the English auction online. Another factor that may influence the online English auction’s popularity is that economic models assume that participants know their precise values for goods, which is not generally true of humans. It has been argued that the English auction’s popularity can, in part, be attributed to the fact that a bidder can often make decisions without precisely computing this value.

The second result is known as the winner’s curse. Again, the seller offers a single item, but this time the buyers have affiliated common values. In this scenario, buyers’ estimates of the object’s value are distributed about the object’s true value. The object is sold to the highest bidder—also the most likely to have overestimated the object’s value. Thus, the highest bidder wins, but ends up paying more than the object is worth.

The third result is perhaps the most significant. It basically says “there is no perfect mechanism.” No auction is incentive compatible, individually rational, efficient, and budget balanced. Unfortunately, this demonstrates that it is not possible to have an auction in which neither buyers nor sellers deviate from truthful behavior unless we subsidize the auction—thereby violating the budget-balance property.

These results provide some guidance when selecting a single-seller, single-item auction, but do not offer much help in more complex environments. In fact, not even the continuous double auction (CDA) is a solved problem; well-known economists continue to discuss possible changes to the rules of major stock exchanges.

Advanced Auctions
When trading multiple resource types, a participant might prefer combinations of resources, or might find that some resources can substitute for one another. In a fragmented market, the desired resources are sold in independent auctions, exposing the participants to risk. Suppose, for example, that a manufacturer requires a particular proportion of two raw materials for its manufacturing process. If forced to buy the materials in separate auctions, the company might be unable to obtain correct amounts of both resources or to ensure their delivery on the same day.

Recent advances in computing technologies enable more advanced combinatorial auctions, which allow agents to express their preferences for combinations of resources. Recent research has focused on both winner determination and price setting components of the combinatorial matching functions.

The analysis of the proposed combinatorial auctions is preliminary. Experimental results with software agents following simple, myopic bidding strategies suggest that these auctions behave quite well. Until a thorough analysis of the incentive properties of these combinatorial auctions is performed, however, we cannot claim that the outcomes obtained with myopic strategies are predictive of solution quality in real applications.

As you can see, the space of possible auction designs is vast, and subtle variations in rules can induce radically different bidding strategies. While our parameterization methods help codify the auction design space, current theory offers little guidance to help a market designer select from among the millions of auction types. The eventual goal of auction research should be a “cookbook” in which a market designer can find the appropriate auction design to satisfy the parameters and objectives of a given situation. Although a complete cookbook is probably unachievable, through theoretical analysis and practical experience we can significantly improve our repertoire.

A Role for Agents
The proliferation of auctions on the Web, and the dynamic nature of auction interactions, argues for the development of intelligent trading agents. Indeed, the nature of the bidding task makes it one of the most relevant applications of agent technologies. First, an agent can monitor and participate in the market continuously. Second, in order to place bids in a fragmented market (or in a combinatorial auction, for that matter), the agent must make com-
A matching function is locally efficient if, based on the information in the bids, no participant can be made better off without making some other agent worse off. This is the standard definition of Pareto efficiency and, in auction literature, is often stated as “no further gains from trade.”

A matching function generates uniform prices if every exchange computed during a clear occurs at the same price. For instance, if an auction selling toasters clears every hour, then every participant with a winning bid at the 11:00 am clear will pay the same price. If the price per unit varies with the number of units or the elements of a bundle, the prices are nonlinear. When participants buy or sell the same quantities at the same time at different prices, the auction implements discriminatory pricing.

A variety of matching policies can be extracted from the literature and from online auctions. The k-double auction implements a locally efficient, uniform price policy in which the parameter k is used to select a price in the range between the maximal and minimal equilibrium prices.1,2 The extremes of this range are referred to as the Mth and (M+1)st prices, where M is equal to the number of buy offers.3 When there is a single unit for sale, the Mth and (M+1)st prices are the first and second prices. The dual-price mechanism essentially implements the same policy but removes the lowest buyer and highest seller from the transaction set.4 This makes the auction incentive-compatible (see the section, “Choosing an Auction Type”) while sacrificing efficiency.

Among the discriminatory policies is the pay-your-bid policy used by some online auctions in multi-unit settings. Generalizations of the stock market are also discriminatory. In the CDA, the price is determined by the bid that is already on the queue, whether it is a buy or sell offer. In effect, the price is determined by the bid that was placed earlier in time. We generalized this to noncontinuous settings, where winning bids are selected from a large collection and then matched. For each matching buy and sell bid, the exchange price will be the price associated with the offer that was submitted earlier.

Even more variation exists in the space of matching functions for combinatorial auctions (see the “Advanced Auctions” section for a brief discussion).

References

plex decisions in real time. Finally, and most importantly, the agent has the autonomy to make decisions that commit its user to future actions.

Consider the decision problem when an agent desires to purchase two units of a particular object. Suppose the agent searches the Web and finds the following three auctions listing the object:

- Auction A lists a single unit. The auction uses typical ascending auction rules with a fixed closing time of $t_A$.
- Auction B lists a single unit. The auction is also an ascending auction, but it closes after time $t_B$ when $\delta_B$ time passes without any new bids.
- Auction C lists five units. It uses a type of multi-unit auction in which each bidder pays the price of the lowest accepted bid. This auction closes after time $t_C$ when $\delta_C$ time passes without any new bids.

The agent must decide whether to attempt to buy two items in auction C, one in C and one in A or B, or one in both A and B. The bidding strategy that accomplishes the selected goal depends on each auction’s announced prices, rules, and relative closing times. Moreover, this decision is not static; the agent’s preference among the goods depends on its expectations of the final prices, which depend on the current price quotes and future actions of the other participants.

It should be noted that some auction sites already offer “agents” that manage bids for you, but these tools are currently very limited. For instance, Egghead.com’s BidWatch simply rebids for you if you are outbid, up to a limit that you prescribe. BidWatch’s automatic rebidding feature raises your bid in a particular auction, but does not reason about substitutable products for sale in other auctions on Egghead’s site, much less on other Web sites.

In the abstract, the architecture of a flexible trading agent can be viewed as a function with three inputs:

- A model of the user’s preferences. The agent should not ask the user how much he or she values every available model of computer monitor, for example, but should ask a few questions from which it can infer a relatively complete preference structure.
A list of auctions relevant to the task and a method for determining each auction’s rules. Current auction search engines (such as GoTo Auctions http://search.auctions.goto.com/) already let users do keyword searches on multiple auction sites. The widespread adoption of XML ontologies for describing products will simplify the search process and improve results. The auction parameterization I described earlier provides the semantic definitions needed to communicate an auction’s rules.

A model of the other participants in the auctions. We expect market models to range between those that account for each individual agent and those that represent only aggregate behavior.

From these inputs, the agent must derive a bidding strategy that maximizes the user’s expected payoff. To date, the majority of investigations into bidding strategies have assumed homogeneous markets.

The Trading Agent Competition represents a domain with heterogeneous, fragmented auctions that present agents with significantly more challenging decision-making problems.

In the near term, you are unlikely to see fully autonomous agents bidding on your behalf. You are more likely to have semiautonomous agents to which you grant limited authority to make bidding decisions, and which must request guidance for other decisions. One reason is that the general population will quite likely feel uncomfortable giving full autonomy to software agents; semiautonomous agents allow users to feel more in control. In addition, it is easier to build semiautonomous agents that know what actions to take along a relatively narrow trajectory, but that ask for help when exceptions occur.

However, semiautonomous agents require more complex interfaces. Once the user specifies preferences, there is no further interaction with a fully autonomous bidding agent until it completes its task. A semiautonomous agent requires an interface that supports complex dialogs with its user. The agent may need to explain its current strategy to the user and request advice on possible alternative strategies. In addition, these dialogs might occur through a wide variety of hardware devices, such as computers, cell phones, and PDAs—each with its own interface constraints.

Acknowledgments
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References

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