Density-based Measure of Reputation of Sellers in Online Auctions

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Abstract. Online auctions are gaining tremendous popularity in recent years. Although providing unprecedent opportunities, online auction sites become an attractive environment for fraud, theft, and deception. Participants of online auctions agree that trustworthy reputation systems are an important factor in fighting dishonest and malicious users. Unfortunately, popular auction sites use only very simple reputation estimation schemes that utilize feedbacks issued reciprocally by users after terminated auctions. Such systems can be easily deceived and do not offer sufficient protection against organized fraud. In this paper we present a novel density-based reputation measure. The new reputation measure uses the topology of seller-buyer connections to derive knowledge about trustworthy sellers. We mine the data on past transactions to discover clusters of connected sellers and for each seller we measure the density of the seller's neighborhood. We perform many experiments on the body of real-world data acquired from a leading Polish provider of online auctions to examine the new measure in detail.

1 Introduction

In the year 2004, e-commerce reached in the USA ca. $18 billion in sales, which made 2% of the total retail sales. It is estimated that over 15% of the entire e-commerce market is being consumed by online auctions. Auctions, which are one of the very first forms of economic activity performed by humans, are experiencing triumphant come-back in electronic form. A model describing online auctions is called customer-to-customer (C2C for short), and its validity and practical usability is well proven by the popularity of online auction sites, such as `www.ebay.com`, `www.ubid.com`, `www.onsale.com`, and many others. An examination of the latest financial data published by eBay, the global leader of online auctioning, reveals an astonishing development: for the second quarter of 2005 eBay reported net revenues of $1.09 billion (40% increase year on year), operating income of $380 million (49% increase year on year), and net income of $290 million (53% increase year on year).

Huge success of online auctions can be attributed to many reasons. Bidders are not constrained by time, bids are placed 24/7 and potential users are given enough time to search for interesting items and bid. The Internet removes also geographical constraints on users, who do not have to physically attend an auction. Large number of sellers and buyers reduces selling costs and potentially offers goods (new and used) at lower prices. Finally, many users describe their bidding experiences as similar to gambling, and offering the highest bid is perceived by them as winning a game.

Online auction sites differ in auction protocols being used. A survey [3] lists main differences: frequency of auctions, bidding, closing, and bumping rules, and types of items. By far the most typical auction protocol is traditional auction (aka English auction), where bidders offer bids on an item until a certain deadline and the highest bid is the winner of the auction. In First Price Sealed Bid auction, each user offers a secret bid. All bids are revealed at the same moment and the highest bid is the winner of the auction. An interesting, yet rare type of auction, is the Dutch auction, when the calling price for an item is subsequently decreased and the first bid is the winner of the auction. Finally, in Vickerey auction users offer secret sealed bids and the winner is the second highest bid. Auction sites differ not only on the auction protocol, but the type of items displayed as well. For instance, on `www.priceline.com` bidders offer bids on commodity items blindly (without knowing the bids of other users) and sellers immediately either accept, or reject the bids.

Apart from offering new and unprecedent possibilities, online auctions provide opportunities for dishonest participants to commit fraud [13]. Online fraud can occur during bidding process and after bidding ends. Popular fraudulent practices include bid shielding and bid shilling. Bid shielding consists in providing artificially high bid for an item, thus discouraging other bidders from competing for an item. At the last moment, the shielder withdraws the bid, so the winner of an auction becomes the second highest bid cooperating with the shielder. Bid shilling consists in using a false bidder identity to drive up the price of an item on behalf of the seller. After the bidding process is over, potential fraud includes refraining from paying (bidder) and sending no merchandise or sending merchandise of lower quality and inconsistent with the offer (seller). Recently, online auction sites reported an increasing number of complaints about "accumulation" fraud: a seller builds up the reputation by selling many low-value merchandise (e.g., small collectibles) over a longer period of time. After such investment a seller presents an offer containing expensive goods (usually video equipment, computer hardware, cellular phones), often using "buy now" mechanism (this is an auction without bidding, a given number of goods is offered at a fixed price and the first bidders to offer that price are the winners of the auction). Needless to say, none of the winners ever gets to receive offered goods. All the above mentioned types of fraud are very dangerous from economical point of view, because they undermine the trust users develop toward the online auction site and decrease the reputation of the service, which can be disastrous to the online auction.

One of the mechanisms to build trust between anonymous participants of online auctions are reputation systems [11]. Trust and fairness of the competition are perceived by auction participants as fundamental issues in developing a successful customer-to-customer market [10]. Furthermore, reputation of sellers has an economically observable and statistically significant effect on price of items [6]. Unfortunately, reputation systems currently used by online auction sites are very simple and do not provide enough protection from malicious users. Typically, reputation of a participant is simply a counter of committed auctions, where each auction is judged by the other party as "positive", "neutral", or "negative". Such simple schema is both unreliable and fraud-prone, because dishonest users can easily deceive it into assigning unfairly high reputation ratings. A seller can create a set of virtual bidders (registering a new user is free and the physical existence of a person is not verified) who will "win" seller's auctions and provide the seller with additional positive feedback points. This technique is known as "ballot stuffing" and it biases the entire system, because unearned reputation allows the seller to obtain more bids and higher prices from other users [8, 12]. In order to better disguise this fraudulent practice, a seller could create a network of auctions between virtual bidders, turning them into a clique. In this way, virtual bidders would pretend to be more credible. Another possibility is to use virtual bidders to provide artificially negative feedbacks to seller's competitors. This technique is referred to as "bad-mouthing" and is more difficult to implement, because it requires to actually win a competitor's auction. Nevertheless, if the gain of driving a competitor out of the market exceeds the investment cost, bad-mouthing can be beneficial.

One thing that should be stressed is the fact, that sellers and buyers are exposed to different types of risk. Sellers can postpone the shipment of an item until the payment is delivered, so the sellers are not threatened financially. On the other hand, buyers pay before receiving an item, unless using a trusted third-party, such as PayPal. The reputation of buyers has little importance for sellers, who are generally interested in receiving payment. Contrary to buyers, seller's reputation is of crucial importance to buyers, who have to decide upon participating in an auction solely based on seller's reputation. In this paper we introduce a novel measure of online auction participant reliability. Our measure is designed only for sellers. We draw inspiration from social network analysis and we discover clusters of densely connected sellers, given thresholds on the minimum price and the minimum number of involved buyers. Our measure can be successfully applied to fight several types of fraud, including "accumulation" fraud. Our original contribution includes the definition of the density-based reputation measure and experimental evaluation of the proposed solution. We test our measure using a large body of real-world data acquired from `www.allegro.pl`, a leader of online auctions in Poland.

1.1 Organization of the Paper

This paper is organized as follows. In Sec. 2 we present the related work on the subject. Section 3 introduces our density-based reputation measure. The properties of the new measure are examined using thorough experiments, the results of those experiments are presented in Sec. 4. We conclude the paper in Sec. 5 with a summary of the future work agenda.

2 Related Work

An anonymous, heterogeneous, and geographically distributed environment for commercial transactions requires an efficient mechanism for building trust between participants. Reputation systems [11] provide users with the means to develop long-term business relationships and receive financial benefit (in more bids and higher prices) for their past honest behavior. Most auction sites use the reputation system developed by eBay, where credibility is expressed as the number of positive feedbacks minus the number of negative feedbacks received by the user [6, 10]. This simple mechanism suffers from several deficiencies, as pointed out in [7]. Feedbacks issued by users are subjective, lack transactional and social context, contain highly asymmetric information (neutral feedbacks are very rare, the spectrum for positive feedbacks is very broad, and negative feedbacks occur only when the quality of service becomes unacceptable, otherwise users refrain from posting a negative feedback in the fear of retaliation).

In recent years several new solutions have been proposed that aim at overcoming at least some of the deficiencies of feedback-based models. An interesting proposal was formulated in [1] where the authors develop a complaint-only trust model. Although originally developed for peer-to-peer environment, this highly decentralized model can be successfully used in online auctions. Another model originating from peer-to-peer environment is PeerTrust [14]. PeerTrust is a complex model consisting of many parameters, such as feedback in terms of satisfaction, number of transactions, credibility of feedback, transaction context, and community context. Method presented in [9] does not use feedbacks to compute the reputation of participants. Instead, it uses a recursive definition of credibility and performs data mining to discover credibility estimation for each participant. A solution presented in [4] tries to prune false feedbacks and accepts only feedbacks that are consistent with the majority of feedbacks received by a given user. The need for a trusted third party is advocated in [2]. The authors propose to introduce a trusted judge that could authorize, identify, and manage the reputation of auction participants. An efficient method for assessing the level of trust between any two individuals based on a small amount of explicit trust/distrust statements per individual is presented in [5]. An interesting comparison of typical fraudulent behavior in online auctions with the abuse of customers by pay-per-call industry in the 1990s is presented in [13]. In the opinion of the author, the ability of online auction business to self-regulate is limited and not adequate to solve the problem, so legislation must be introduced to guarantee sufficient customer protection.

In this paper we focus on a novel measure that can be used to characterize participants of online auctions. Specifically, we are interested in discovering hidden patterns that can be used to estimate the reputation of each seller. In order to achieve this, we measure the density of each seller's neighborhood. Our measure is flexible and can be successfully adapted to many different environments. The most important feature of our method is the fact, that it is fraud-resistant and difficult to deceive. In the next section we present our measure of reputation in detail.

3 Density-based Reputation Measure

The main drawback of all feedback-based reputation systems is the fact that the reputation estimation for a given user is strongly influenced by the reputation of users directly involved in auctions with the user. This enables dishonest participants to artificially inflate their reputation estimates. Therefore, we propose a novel reputation measure for sellers, which computes the reputation of a given seller based on the reputation of other "similar" sellers.

Given a set of sellers $S = \{s_1, s_2, \ldots, s_m\}$. Two sellers s_i and s_j are *linked* if there are at least *min_buyers* who committed an auction with sellers s_i and s_j, and the closing price for each auction was at least *min_value*. The number n_{ij} of such buyers is called the *strength* of the link and is denoted by $|link\,(s_i, s_j)|$. The *neighborhood* $N(s_i)$ of a seller s_i consists of sellers $\{s_j\}$, such that the seller s_i is linked with s_j, given user-defined thresholds *min_buyers* and *min_value*. The cardinality of the neighborhood $N(s_i)$ is called the *density* of the neighborhood. The rationale behind user-defined thresholds is the following: *min_buyers* selects sellers with significant number of sales, and *min_value* prunes low-value transactions. The density measure can be interpreted as follows: a buyer who buys from sellers s_i and s_j acknowledges the quality of both sellers. Unexperienced buyers are unlikely to link many sellers, these are rather experienced buyers who are used to link sellers. In this way the density-based measure discards unreliable information from unexperienced buyers. The fact that two sellers are linked indicates that either they trade similar and popular goods (such as music or books), or that their offer is complementary (like bicycles and bicycle add-ons). Obviously, a link between two sellers may by coincidental and may not bear any useful information. Nevertheless, high density of a seller is a good indicator of seller's trustworthiness. Another important issue is the type of a cluster to which a seller is linked. Density-based reputation measure discovers natural groupings of sellers around product categories, thus allowing to quickly discover "accumulation" fraud, when a seller suddenly changes their main product category.

The density-based reputation measure does not consider the strength of the link between any two sellers, only the density of a given seller's neighborhood. In order to distinguish between strongly and weakly linked sellers we introduce another reputation measure, called *score*, defined as

$$score\,(s_i) = \sum_{s_j \in N(s_i)} density\,(s_j) * \log_{min\_buyers} |link\,(s_i, s_j)|$$

The score measure uses the density of each seller in the neighborhood of the current seller and multiplies it by the strength of the link between the two sellers. The logarithm is used to reduce the impact of very strong links between sellers.

The density-based reputation measure is very resistant to fraud and manipulation. Let us consider a malicious seller trying to enter the cluster of reliable sellers. Linking to a single trustworthy seller requires to create *min_buyers* and investing at least *min_buyers*∗*min_value* in winning auctions of a trustworthy seller. Still, this links only to a single seller and places the cheater in the outskirts of the cluster. In order to receive higher density the cheater has to repeat this procedure several times. We attribute this feature of the density-based reputation measure to the fact that it uses other sellers to rate a current seller, rather than using information from buyers. We believe that it is much more difficult for cheaters to manipulate other sellers than to create virtual bidders and use them to inflate cheater's reputation.

4 Experimental Results

The data have been acquired from `www.allegro.pl`, Polish leader of online auctions. The dataset consists of 440 000 participants, 400 000 auctions, and 1 400 000 bids. The number of participants is greater than the number of auctions, because for each participant their highest bid is stored, whether it was the winning bid or not. Therefore, we have data on some participants who did not win any auction. Analyzed dataset is a small subset of the original data and it has been created in the following way: 10 000 sellers have been selected, and for this seed set all their auctions from a period of six months and participants of these auctions have been collected. Analogously, 10 000 buyers have been selected randomly and a similar procedure has been applied to this seed set. Altogether, complete information on 20 000 participants was available. Data were stored and preprocessed using Oracle 10g database.

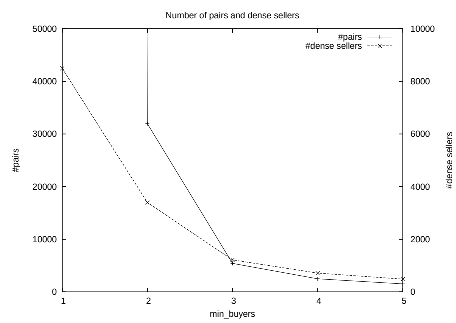


Fig. 1.

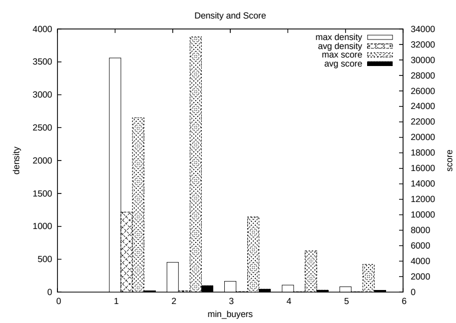


Fig. 2.

Figure 1 presents the number of linked pairs of sellers and the number of dense sellers when increasing the value of the *min_buyers* threshold. As can be seen, even for small threshold value the number of pairs and the number of dense sellers becomes manageable. Changes of maximum and average values of density and score for sellers when the value of *min_buyers* threshold change are depicted in Fig. 2. Figures 3 and 4 present analogous results for varying the values of the *min_price* threshold.

Two examples of density distribution are presented in Fig. 5 (no limits on *min_buyers* and *min_price*) and Fig. 6 (*min_buyers*=2 *min_price*=\$20). Interestingly, when no thresholds are defined, two clusters of sellers are visible. The

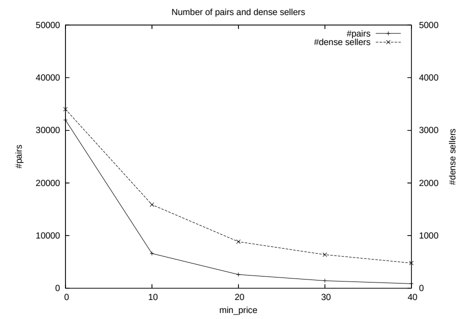


Fig. 3.

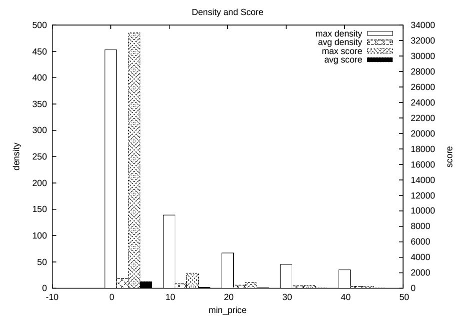


Fig. 4.

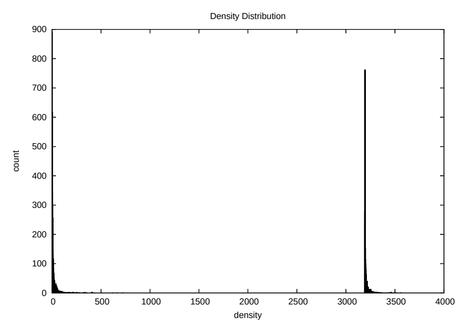


Fig. 5.

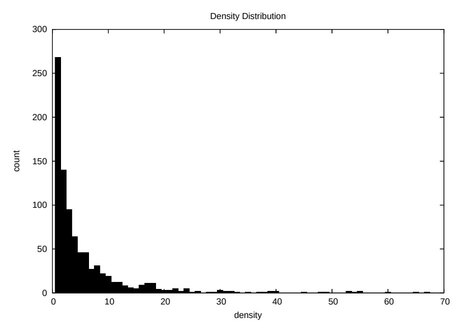


Fig. 6.

majority of sellers are characterized by the density from the range $\langle 1, 500\rangle$, but there is also a small group of very densely connected sellers, and their density is $\langle 3200, 3500\rangle$. Average density is 1217 and 8493 sellers (85% of the entire population) turned out to be dense. When thresholds are set, the average density drops to 5.9 and the number of dense sellers is 885 (8.8% of the entire population). One might argue that the *min_price* threshold is set too prohibitively, but the average price of items in the mined dataset is close to $30, so we rather believe, that the algorithm really discovers the set of most important and credible sellers.

An interesting question is how does the new density-based measure relate to traditional reputation rating computed as the aggregation of positive and negative feedbacks. The average rating distribution with respect to density is presented in Fig. 7 (*min_buyers*=3, *min_price*=0) and Fig. 8 (*min_buyers*=2, *min_price*=$30). In general, higher density is a good indicator of high rating, but this relationship is not linear, specially when *min_price* threshold is set to prune out low value transactions. Fig. 9 (*min_buyers*=2, *min_price*=0) and Fig. 10 (*min_buyers*=2, *min_price*=$10) show the projection of average rating vs density. Many high rated sellers have low density, which is even more visible when *min_price* is set. Sellers with high ratings are usually trading popular goods that are not expensive, so *min_price* threshold is punishing them. Similar analysis

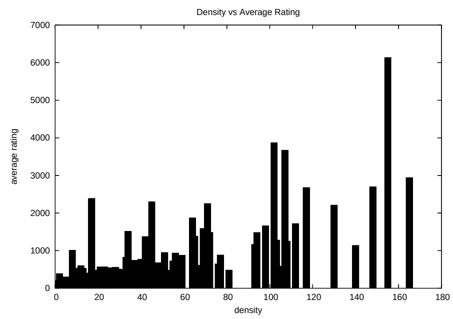


Fig. 7.

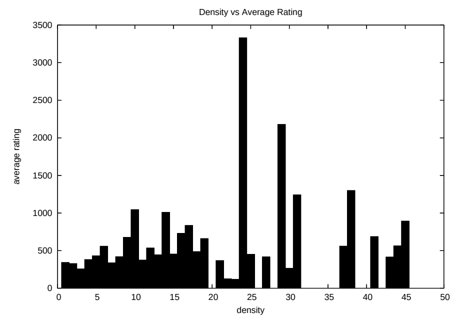


Fig. 8.

of average rating vs score is presented in Fig. 11 (*min_buyers*=3, *min_price*=0) and Fig. 12 (*min_buyers*=2, *min_price*=\$20). These figures reveal a shift along the x-axis. This suggests that the sellers with low density and high rating have much higher average strength of the link than densely connected sellers.

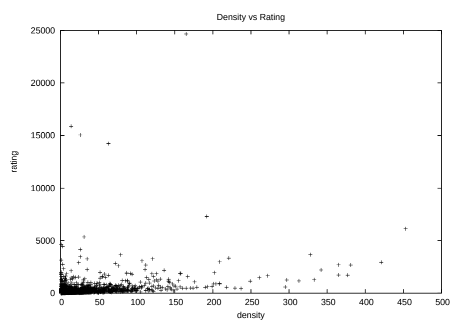


Fig. 9.

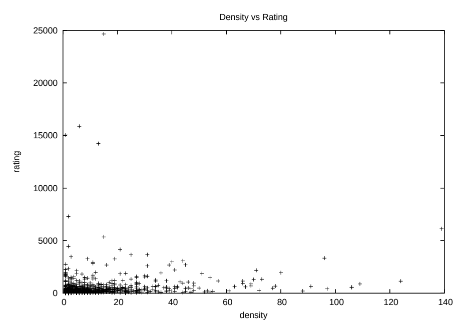
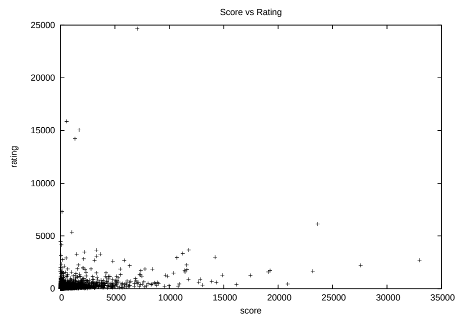


Fig. 10.

The distribution of average price of offered items with respect to density is depicted in Fig. 13 (*min_buyers*=3, *min_price*=0) and Fig. 14 (*min_buyers*=2, *min_price*=\$10) (on figures prices are given in Polish zloty). Surprisingly, there is no clear evidence that higher density has any impact on the closing price reached by sellers.

Finally, Fig. 15 (*min_buyers*=4, *min_price*=0) and Fig. 16 (*min_buyers*=2, *min_price*=\$30) present the distribution of average number of sales with respect to density. This time it is easily noticeable that highly dense sellers enjoy much larger volume of sales. This fact, more than the distribution of average price of items, convinces us, that density is a good predictor of future performance of a participant of an online auction.



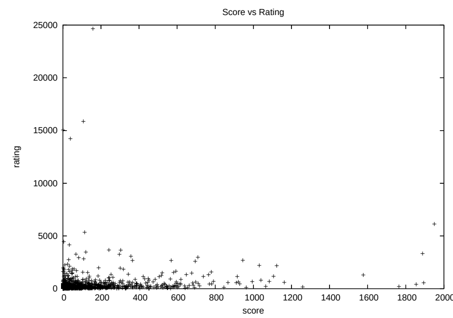
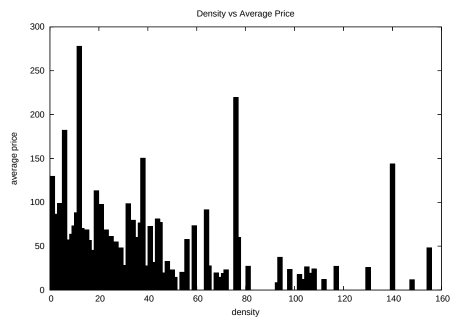


Fig. 11.

Fig. 12.



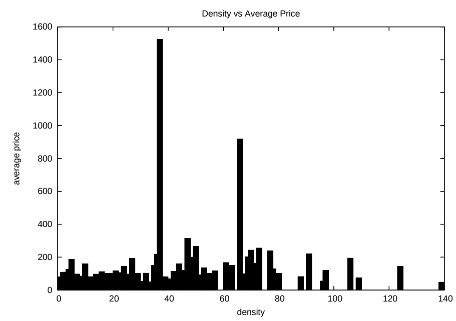


Fig. 13.

Fig. 14.

5 Conclusions

In this paper we have introduced a novel reputation measure for participants of online auctions. Our measure considers the network of seller-buyer connections and mines the topology of the network to derive useful knowledge about users. Discovered clusters of densely connected sellers can be used as a predictive of future performance of a user, thus providing additional insight into the data. We believe, that the density of a seller can be successfully used as an indicator of seller's reliability. Main advantages of the proposed solution include resistance to manipulation, ability to discover complex fraudulent activities, and practical usability proved by experiments. The support exhibited by our commercial partners encourages us to follow the work in this area of research. Our future work agenda includes other models of user reputation, efficient use of negative and lacking feedbacks, and thorough investigation of the properties of clusters of sellers.

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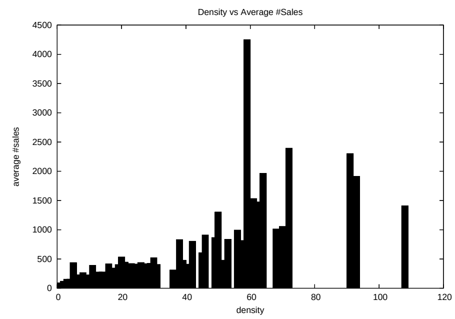

Fig. 15.

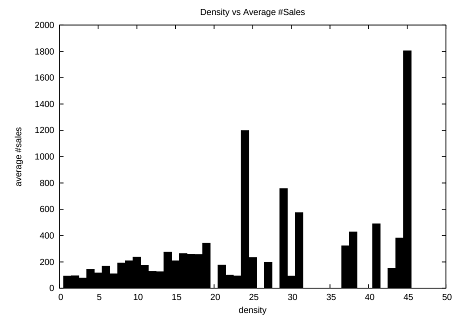

Fig. 16.

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