Predictive Modeling for Collections of Accounts Receivable

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ABSTRACT
It is commonly agreed that accounts receivable (AR) can be a source of financial difficulty for firms when they are not efficiently managed and are underperforming. Experience across multiple industries shows that effective management of AR and overall financial performance of firms are positively correlated. In this paper we address the problem of reducing outstanding receivables through improvements in the collections strategy. Specifically, we demonstrate how supervised learning can be used to build models for predicting the payment outcomes of newly-created invoices, thus enabling customized collection actions tailored for each invoice or customer. Our models can predict with high accuracy if an invoice will be paid on time or not and can provide estimates of the magnitude of the delay. We illustrate our techniques in the context of transaction data from multiple firms.

Categories and Subject Descriptors
G.3 [**Probability and Statistics**]: correlation and regression analysis, experimental design.
I.3 [**Simulation and Modeling**]: Applications.
J.1 [**Administrative Data Processing**]: Business, Financial.

General Terms
Design, Economics, Experimentation, Performance.

Keywords
Accounts Receivable, Payment Collection, Order to Cash, Invoice to Cash, Predictive Modeling, Knowledge Discovery.

1. INTRODUCTION
The Order-to-Cash (O2C) process describes a composite business process that comprises the necessary steps to fulfill an order for a good or service, from order entry to payment receipt. While the number and nature of such steps may vary depending on the type and size of the firm, most O2C processes follow a similar high-level workflow as illustrated in Figure 1.

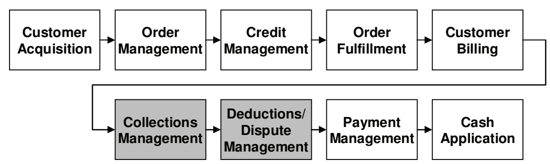

Figure 1. Typical order-to-cash process

In this paper we concentrate on the two highlighted steps of Figure 1. These steps constitute the core of the collections activities and deal with account prioritization, customer contact activities, collection calls, escalation, and resolution of disputes. Most often, these steps are processed manually and hence, slow, expensive, and inaccurate, despite their importance to the business. Moreover, the collection actions are typically generic and do not take into account customer specifics, e.g., all customers are contacted at fixed intervals, even though some have always paid on time; while it is generally true that the later a customer is contacted the less likely the invoices will get paid on time, repeated contacting of "good" customers may lead to lower customer satisfaction. Such inefficiencies in current practices lead to significant delays in AR collections or even to failure to collect before write-off deadlines.

The effectiveness of AR collections can be significantly improved through better management of the collection steps. For instance, taking preemptive actions on invoices that are likely to become delinquent can drive down the collection time. Furthermore, by prioritizing delinquent invoices for actions based on the expected time of payment, one can optimize the use of collections resources. In this paper we focus on the task of predicting the payment outcomes of newly-created invoices, thus enabling more effective collections management.

2. INVOICE OUTCOME PREDICTION
There are many metrics used to measure the collection effectiveness of a firm [1]. For instance, Average Days Delinquent measures the average time from invoice due date to the paid date, i.e., the average days invoices are overdue. A related metric, Days

Sales Outstanding (DSO) expresses the average time in days that receivables are outstanding, computed as:

$$\text{DSO} = \frac{\text{Accounts Receivable} * \text{Number of Days}}{\text{Total Credit Sales}}$$

Most commonly used metrics are functions of the time taken to collect on invoices. If one can predict the outcome of an invoice, one can use this information to drive the collection process so as to improve on a desired collection metric. For instance, if one can identify invoices that are likely to be delinquent at the time of creation, one can attempt to reduce the time to collection by pro-actively trying to collect on these invoices. Typically, collections departments wait until invoices are delinquent to start taking collection actions, such as sending out reminders or making phone calls. However, one could significantly benefit from preemptively contacting potentially delinquent accounts. Furthermore, even after an invoice is past due, it is beneficial to know which invoices are likely to be paid sooner than later, if no action is taken. Given that resources for collections activities are often limited, one may choose to prioritize invoices based on estimating how late a payment will be; e.g., it makes more business sense to contact a customer who is likely to pay 90 days late, than one who would pay within 30 days without contact.

We formulate the invoice outcome prediction task as a supervised learning problem: given instances of past invoices and their outcomes, build a model that can predict when a newly-created invoice will be paid, if no action is taken. In particular, each instance is classified into one of five classes: on time, 1-30 days late, 31-60 days late, 61-90 days late, and more than 90 days late (or 90+ days late). Data instances correspond to features representing invoices, which are described in detail below.

This formulation corresponds to using the Average Days Delinquent as the collections performance metric. However, if the objective is to maximize a different performance metric, that can be done by using an alternative target (class) variable that is correlated with this metric. For example, one may use the Collection Effectiveness Index (CEI), which compares what was collected in a given period to what was available to collect, defined as:

$$\text{CEI} = \frac{(\text{Begin Receivables} + \text{Credit Sales} - \text{End Total Receivables}) * 100}{\text{Begin Receivables} + \text{Credit Sales} - \text{End Current Receivables}}$$

In this case, invoices can be labeled based on the actual amounts collected in a specified time period.

2.1 Data Preprocessing

The analysis in this paper is done on invoice records for four firms, including two fortune 500 companies. Three of these firms are competitive in the markets for supplying high-tech equipments for telecommunication, networking, and IT services. The fourth firm specializes in online advertising placement and scheduling services. The summary of invoice records is presented in Table 1. These data sets cover invoices created from March 2004 to February 2005. When learning from these data sets, we differentiate invoices of first time customers from those of returning customers, because their payment behaviors are very different, moreover, there is additional historical information available for invoices of returning customers. In this paper, we use term *first-time invoices* to refer to the invoices from first-time customers. Likewise, *returning invoices* are invoices from returning customers. Table 1 shows that the majority of invoices of three firms (A, B and D) are returning invoices while C has the majority of its invoices billed to first time customers.

Table 1. Summary of data sets

Firm	# of invoices	# of returning invoices (%)	# of first-time invoices
A	40908	32871 (80.35)	8037
B	109589	94047 (85.82)	15542
C	22701	5564 (24.51)	17137
D	8474	5873 (69.31)	2601

Our input data consists of a set of invoices at the end of the collections cycle. Each invoice is described by 54 features that capture information such as order details, terms and conditions, sales representative information, etc. We begin by eliminating features that are specific to an invoice, such as invoice IDs. We then remove leakage variables – features that provide information about the class label that one would not have at the time of creation of an invoice, such as invoice closing date and number of touches. For ease of modeling, we also exclude categorical features that have too many distinct values, such as customer groups and customer names. Finally, we filter out features that have too many missing values or have unique values, such as invoice types. This leaves us with only three meaningful features, named as invoice-level features that represent an invoice (see Table 2): invoice base amount, payment terms, and invoice category. Given the number of days delinquent, computed based on invoice close date and due date, each invoice/instance is labeled with one of the five class labels: on time, 1-30 days late, 31-60 days late, 61-90 days late, and more than 90 days late (or 90+ days late).

The three invoice-level features are insufficient for effective modeling. However, a large number of invoices are for returning customers, which is especially true for firms with large accounts such as A and B, where more than 80% of the invoices are for returning customers. Based on this observation, we develop additional features that (a) capture the transaction history of a customer, e.g., the percentage of invoices paid late in the past; and (b) reflect the current status of the customer's accounts, e.g. the sum of base amounts of all invoices currently outstanding. Table 2 lists all these historical and aggregate features that are generated (features numbered 4-17). These features provide a significant amount of information that can be leveraged for predicting the outcome on a new invoice. However, such information is not available for first-time customers, or for the first invoices of customers. Therefore, in this paper we focus primarily on building predictive models for the invoices of returning customers. However, for completeness, in Section 3.3 we also discuss the task of modeling on invoices without history.

Table 2. Summary of features

No.	Feature	Description
1.	Invoice base amount	Base amount of a invoice
2.	Payment term	The deadline of payment due
3.	Category	Indicator of whether invoice is under dispute or not
4.	Number of total paid invoices	Number of paid invoices prior to the creation date of a new invoice of a customer.
5.	Number of invoices that were paid ate	Number of invoices which were paid late prior to the creation date of a new invoice of a customer
6.	Ratio of paid invoices that were late	Ratio of 5. over 4.
7.	Sum of the base amount of total paid invoices	The sum of the base amount from all the paid invoices prior to a new invoice for a customer
8.	Sum of the base amount of invoices that were paid late	The sum of the base amount from all the paid invoices which were late prior to a new invoice for a customer.
9.	Ratio of sum of paid base amount that were late	Ratio of 8. over 7.
10.	Average days late of paid invoices being late.	Average days late of all paid invoices that were late prior to a new invoice for a customer
11.	Number of total outstanding invoices	Number of the outstanding invoices prior to the creation date of a new invoice of a customer.
12.	Number of outstanding invoices that were already late	Number of the outstanding invoices which were late prior to the creation date of a new invoice of a customer
13.	Ratio of outstanding invoices that were late	Ratio of 12. over 11.
14.	Sum of the base amount of total outstanding invoices	The sum of the base amount from all the outstanding invoices prior to a new invoice for a customer
15.	Sum of the base amount of outstanding invoices that were late	The sum of the base amount from all the outstanding invoices which were late prior to a new invoice for a customer.
16.	Ratio of sum of outstanding base amount that were late	Ratio of 15. over 14.
17.	Average days late of outstanding invoices being late.	Average days late of all outstanding invoices that were late prior to a new invoice for a customer

3. APPROACH

The task we formulated is a typical supervised classification problem: given a set of data instances (invoices) represented by a set of features and class labels, build a model that can classify a new instance into one of five target classes – on time, 1-30 days late, 31-60 days late, 61-90 days late, and more than 90 (or 90+) days late. In the following sections we will discuss the different settings for invoice prediction we studied.

In pilot studies, we compared the following classification algorithms for our domain – C4.5 decision tree induction [2], Naïve Bayes [3], and the PART algorithm [4] (described below). Among these algorithms, PART performed the best in terms of classification accuracy. PART is a rule learner that uses a separate-and-conquer approach. It builds a rule, removes the instances that it covers, and repeats this process recursively on the remaining instances until there are none left. To produce each rule, PART builds a *partial* pruned decision trees in a manner similar to C4.5, and the leaf with the largest coverage is made into the rule while the rest of the tree is discarded. To avoid over-fitting in our experiments, we only consider rules that cover a minimum of 100 instances.

In addition to learning accurate classifiers, PART is a good choice for our domain, because it can handle missing values, nominal values, and it produces comprehensible models in the form of human-readable decision lists. For all experiments described below, we present results from using the PART algorithm. Experiments were run using 10-fold cross validation, and classification accuracy is reported as the performance metric. Where relevant, we report the accuracy in predicting a specific class. As a point of reference, we also report the accuracy of the majority-class predictor, i.e., a classifier that always predicts the class most represented in the training data.

3.1 Using Historical Data

In Section 2.1 we describe the construction of historical and aggregate features. We conjecture that these features provide a significant amount of information beyond the simple invoice-level features. We validate this hypothesis by comparing models built using only invoice-level features to models built using both invoice and historical features. Experiments were conducted using only data for invoices of returning customers, because historical features are only meaningful for these invoices.

The prediction results are summarized in Table 3. We observe that even with just the three invoice-level features we can predict the payment outcome of an invoice more accurately than predicting the majority class. However, this improvement is marginal in some cases, as in B and D, where the difference in accuracy is less than 1 percent. Furthermore, incorporating historical features into the data gives rise to a substantial increase in prediction accuracies for all four firms. We observe improvements ranging from 4 (B) to 20 percent (C). Overall, the model accuracies are significantly better than the baseline. As such, using these predictions to drive workflow of collections is likely to perform a lot better than current practices that treat all invoices equally. We are currently designing a controlled live experiment to demonstrate this.

Table 3. Using historic date to predict returning invoice payment behavior

Firm	Feature Category	Accuracy	Majority Class Accuracy
A	Invoice	68.24	60.22
	Invoice+History	81.38	
B	Invoice	84.72	84.58
	Invoice+History	88.28	
C	Invoice	49.68	46.10
	Invoice+History	66.46	
D	Invoice	58.79	57.82
	Invoice+History	70.87	

3.2 Cost-sensitive Learning

In accounts receivable collection, the main reason for categorizing the payment behavior of invoices is to be able to customize monitoring and collection activities according to their past due behavior. One of the critical measurements of collection performance is Average Days Delinquent. As such, we have focused our modeling on predicting the expected time in payment. However, as discussed in Section 2, there are other Key Performance Indicators (KPIs) that are often used to measure collection success. For instance, several of our firms have a KPI objective to keep the number of invoices that are more than 90 days overdue below a specified limit. These invoices are potentially bad debt accounts, which require special decisions and set of actions to collect payments for these accounts. If this set of invoices can be identified at an early stage of the lifecycle of the invoices, one can preemptively deal with potentially bad debt accounts before they turn into debt or even get written off.

To attain this objective we build models that are focused on being able to predict accurately for the 90+ class. By default, classification algorithms assume that all classes are equally important. However, the penalty for predicting an invoice will be paid on time when in fact it will more than 90 days overdue, is usually higher than the reverse. This task is further compounded by the fact that these high-risk invoices are under-represented in the data. This can be seen in the distribution of invoices for Firm A in Figure 2, where the total number of 90+ invoices is only 3% of the entire data set. The data for the three other firms show a similar imbalance in the data.

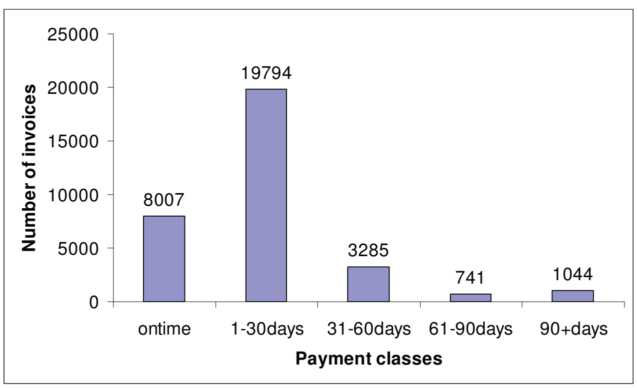

Figure 2. Invoice distribution of Firm A

To address the different misclassifications costs, we use instance re-weighting, which is a common approach in cost-sensitive learning. As input, we provide a misclassification cost matrix, such as the one shown in the second column of Table 4. Each row and each column corresponds to target classes. Each cell corresponds to the cost of misclassifying the row class as the column class. The diagonal corresponds to correct classifications and hence are all zero. By default, all costs, other than the diagonal, are set to one. Instances belonging to particular class are re-weighted proportionally to the sum of its misclassification costs.

Table 4 reports our results on the four firms for one such cost matrix. We present both the overall accuracy, as well the true positive (TP) rate of the 90+ class. The results show that instance re-weighting is a very effective way of dealing with the high class imbalance in this data – we can more than double the TP rate of the 90+ class without much loss to overall accuracy as is seen for Firm B.

Table 4. Cost sensitive prediction accuracy for four firms. The standard cost matrix corresponds to equal misclassification costs.

Firm	Cost Matrix	Accuracy	90+ Accuracy
A	Standard	81.38	73.6
	a b c d e 0 1 1 1 1| a = on time 1 0 1 1 1| b = 1-30 days 1 1 0 1 1| c = 31-60 days 1 1 1 0 1| d = 61-90 days 5 4 3 2 0| e = 90+ days	81.27	79.7
B	Standard	88.28	18.6
	Same as A	88.09	42.6
C	Standard	64.11	29.6
	Same as A	63.61	45.1
D	Standard	62.86	25.6
	Same as A	59.15	60.4

To further explore this, we ran additional experiments using different costs matrices. The results for Firm A, for three different cost matrices are summarized in Table 5. Results show that by increasing the cost of misclassifying the 90+ class, we can get the learning algorithm to focus on building classifiers that are more accurate at predicting this class. In fact, with high enough misclassification costs the classifier can learn to predict the 90+ class with more than 95% accuracy. As expected, this comes at a trade-off on overall classification accuracy. This trade-off can be balanced based on the desired performance objectives.

Table 5. Cost sensitive prediction accuracy for Firm A

Cost Matrix	Accuracy	90+ Accuracy
a b c d e 0 1 1 1 1| a = on time 1 0 1 1 1| b = 1-30 days 1 1 0 1 1| c = 31-60 days 1 1 1 0 1| d = 61-90 days 5 4 3 2 0| e = 90+ days	81.27	79.7
0 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 0 1 50 4 3 2 0	78.27	87.9
0 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 0 1 500 4 3 2 0	62.32	95.7

The cost matrix can be specified based on the actual costs associated with the incorrect prediction in practice. For instance, if a 90+ invoice is incorrectly labeled as on time invoice, then the associated cost includes the interest loss because of potential customer debt. The loss due to misclassification need not always be quantified by monetary value. For instance, if an on-time instance is misclassified as a 90+ instance, it is likely that the customer will be contacted even before the due date. Apart, from the wasted cost of contacting a customer who is going to pay on time, there is the additional risk of damaging the customer relationship. The trade-offs between expected loss in revenue and customer satisfaction are quite complex and vary from firm to firm. In our current modeling, we only concern ourselves with the misclassification of 90+ instances into other class labels. However, the same methodology can be used to accommodate other cost-structure that may represent alternative KPI objectives.

3.3 Prediction for New Accounts

As discussed in Section 2.1 we have focused primarily on invoices of returning customers, because of the richness of historical data that is not present in the invoice-level features. However, in some cases it may be possible to get additional information on the customers themselves, which may make it possible to even build models for invoices of first-time customers.

Invoice payment risk, to a large extent, may depend on the customer's financial capability and willingness to pay. Such factors may be influenced by customer credit worthiness, organizational profile, business market profile, etc. These factors are captured in a set of customer features, such as credit limit, segment, and region. For Firm A, such customer-level attributes are actually collected and are readily available for modeling. We selected 11 such attributes after going through the same feature selection mechanism described in Section 2.1.

For Firm A, we now have three sets of features, namely invoice-level, historical and customer-level features. We run experiments as before, on four combinations of these feature sets, on three versions of the Firm A data – returning invoices, first-time invoice and all invoices. These results are summarized in Table 6. Results show that having customer features boosts prediction accuracy from 66% to 72% for first-time invoices. Though this accuracy is not as high as when using historical features; it does demonstrate that the customer-level features provide some information regarding the collectibility of invoices.

We further investigate the effectiveness of having customer features for invoices of returning customers. As seen in Table 6, adding customer features to invoice features improves prediction accuracy compared to only using invoice features, even for returning customer. However, if we replace customer features with historical features, there is an additional 9% increase in accuracy. Clearly, historical features are more effective than customer features in determining the outcome of invoices. Having all three feature sets together achieves the best prediction accuracy; however this is only a marginal improvement over using the invoice and historical features. These results motivate building separate models for prediction for returning customers; and shows that when customer information is available one can also build good models for first-time invoices.

Table 6. Prediction accuracy of Firm A

Features	All invoices (accuracy)	Returning invoices (accuracy)	First-time invoices (accuracy)
Invoice	65.95	68.24	66.33
Invoice+Customer	70.37	72.29	72.24
Invoice+History	78.57	81.38	N/A
Invoice+Customer +History	79.80	81.77	N/A

3.4 Unified Model vs. Firm-specific Models

For experiments in previous sections we built one model for each firm. However, in principle, we could build one unified model combining the data from all firms. Building such a model could help generalize better and learn behaviors and patterns that are common to all firms. Combining the data from all firms would also provide a lot more training data, which usually improves modeling. To test this conjecture, we build a unified model combining all training sets, and present results using this model to predict for invoices belonging to each firm. We compare this model with training individual models for each firm.

The results in Table 7 indicate that building separate firm models actually achieve better prediction accuracy than using one unified model. This seems to suggest that the collection processes and behaviors of invoices for each firm are somewhat different. For instance, Firm A, B and D tend to contact customers for more than 93% of invoices, while Firm C contacts customers for only 32% of the invoices. The invoice payment behavior is also quite varied for firms, e.g., 54% of invoices of Firm C are paid on time, while only 25% of invoices for Firm B are on time. These and other observations lead us to believe that it is more valuable to build individual prediction models for each firm, which is also consistent with the results we obtained from the modeling experiments.

Table 7. Prediction accuracy of unified model vs. firm-specific models

Test Data	Accuracy of unified model	Accuracy of firm model
Firm A	81.78	82.47
Firm B	88.51	88.89
Firm C	62.19	65.44
Firm D	64.81	65.10

4. RELATED WORK

There are a number of vendors offering pre-packaged solutions for order-to-cash. Examples are Oracle's *e-Business Suite Special Edition Order Management* [5] and SAP's *Order-to-Cash Management for Wholesale Distribution* [6]. Oracle's solution provides information visibility and reporting capabilities. SAP's solution supports collections and customer relationship management. To our best knowledge, none of such solutions incorporates analytics, especially predictive modeling for improved prioritization of invoices or for customer ranking, with subsequence collection process optimization.

Predictive modeling approaches are widely used in a number of related domains, such as credit management and tax collection. Talgentra and Accenture are two representative examples. To better manage customer credit, Talgentra proposes to use predictive modeling approach [7]. They consider the use of prediction techniques such as decision trees, association rules, and neural networks in order to build customer models. These models are then used to predict collection probabilities, most suitable payment terms, and schedules for a given customer. Accenture uses assignment rules to optimize workforce utilization (re-assigning staff to tasks as field collection, telephone collection, customer service) for tax collection. The rules are generated based on probable collection outcomes by learning from historic performance numbers and expected new accounts receivable [8]. However, the details to generate these rules are not given. In fact, since, predictive modeling approaches vary based on the problem domains, these solutions are unlikely to sufficient to address issues for O2C payment collection.

There is a small body of work in the O2C domain. One such work can be found in [9], in which, a model is used to predict collection amounts on customer accounts based on learned relationships among known variables. The predictive models are generated with historical information on customers, on event patterns for customers, or on collectors' notes for a customer. Neural networks are used as one of the approaches for predictive modeling. While the approach focuses on collection amounts prediction, we believe both amounts and delays are important for collection decision making. Another difference is that we can tackle collections not only at the customer level, but also at the invoice level.

The most closely related work is by Bailey et al. [12]. The authors discuss possible improvements over Providian's cash collection strategy. They analyze various strategies for prioritizing collection calls and propose to use predictive modeling based on binary logistic regression and discriminative analysis to determine which clients to "outsource" (i.e., which customer accounts to hand over to an outside collections agency for further collection processing). The authors present some preliminary results of their modeling approach in the form of analytics assuming certain prediction accuracies and collection returns. Their work is complementary to ours in that they deal with the cost/benefit decisions that would need to be made once the priority/risk of each collection item is determined. Our work, on the other hand, tries to assess which techniques are best suited for determining this priority/risk.

Other relevant work comes from a number of new companies that provide rule engines to prioritize invoices to maximize cash flow. For instance, cforia [10], a 2002 start-up, offers various collection management solutions. On their website, they claim among other AR process improvements, a new way of automatically prioritizing invoices based on a rule-based system. They claim that "cforia's rules engine automatically sends the collections and deductions teams prioritized ticklers to maximize cash flow." Another start-up, IntelligentResults [11], offers a platform called *PREDIGY*, which provides a variety of business analytics capabilities. For example, beside the manual creation of business rules, PREDIGY also allows deriving strategies and models via automatic data clustering and segmentation. Moreover, they offer integrated testing and simulation tools for verifying the effectiveness of the derived rules. These solutions are helpful to create, use and validate the rules, once rules are known. However, there is no evidence that these solutions enable automatic rule generation by learning from the past, which is the core of our approach in this paper.

5. CONCLUSIONS

In this paper, we have presented a supervised learning approach and the corresponding results in the context of AR collections. We developed a set of aggregated features which capture historical payment behavior for each customer. Our results show that having this set of features enhances the prediction accuracy significantly, and it is more valuable in predicting payment delays for invoices from returning customers than using customer features. However, we also observed that customer features play an important role in the prediction of payment delays when no historical information is available, e.g., for invoices from first time customers. We demonstrate that by using cost-sensitive learning, we are able to improve prediction accuracy particularly for high risk invoices, which are under-presented in the data sets. Finally, we compared the prediction performance of a single generic model with that of firm-specific models and we showed that the latter leads to better prediction accuracy.

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