Predictive Models for Enhanced Audit Selection: The Texas Audit Scoring System

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Agenda

- Data Mining Overview
- Audit Selection Problem
- Data Mining for Audit Selection
  - Texas Audit Select System
  - Predictive Models
  - Results
- Final Remarks
Data Mining Overview

- Data Mining
  - “... is the process of discovering meaningful new correlations, patterns and trends by sifting through large amounts of data stored in repositories, using pattern recognition technologies as well as statistical and mathematical techniques.” (Gartner Group)

- Mature, widely accepted in:
  - Commercial (e.g., CRM, credit-scoring, and ‘eTail’)
  - Public sector (e.g., payment error detection, law enforcement, logistics, and homeland security)

Cross Industry Standard Process for Data Mining (CRISP-DM)

- launched 1996
- 200 members across vendor, integrator/consultant, and user communities
- application/tool/vendor neutral
- focus on business issues, guidance framework, and comfort factor
- www.crisp-dm.org
Data Mining Overview - Modeling

- Data driven
- Supervised techniques
  - modeling relationships between known targets and potentially relevant inputs using training data
  - for example, Neural Networks

- Unsupervised techniques
  - ‘discovering’ patterns (associations, sequences, segments)
  - for example, Clustering
  - Clusters/groups/segments of similar returns
  - ‘small’ clusters can be interesting

Audit Selection Challenge

Problem:

Maximizing tax collection and compliance with limited auditing resources.

Texas Statistics:

- Active Sales Tax Taxpayers: 761,434
- Available Auditors: 380
- Yearly Audits Completed: ~5,200
- % of active taxpayers audited yearly: 0.7%
Finding the “golden needle”

- A small percentage of audits account for a very large proportion of assessments
  - Total assessed tax adjustments from audits:
    - Approximately $90M (2002)
    - 40% from the top 0.5% of completed audits

- One fifth of resources spent on no-change audits
  - Percentage of “no-change” audits: 35-40%
    - No-change audits account for 15-20% of hours

Audit Selection Strategies

Traditional audit selection strategies:

- Top Contributors
  - Focus on reported tax dollars, large businesses
  - Texas “Priority 1” program

- Prior Audits
  - Focus on prior audit outcome
  - Texas “Prior Productive” program
Why Data Mining?

- Traditional audit selection criteria typically leverage a single metric:
  - Total tax reported
  - Prior audit results
  - Percent deductions, SIC, Age of the business, etc.

- Difficult to identify and leverage patterns from audit outcome data:
  - Which “metrics” are more relevant?
  - Profiling the “golden needles” to find more of those…

Multi-Dimensional Approach

Data Mining can leverage dozens of taxpayer metrics and characteristics for enhanced audit selection.

TAXPAYER PROFILE:
- Gross Sales
- Deductions
- SIC
- Wages
- Other Tax Types
- Prior Audits
- Years in Business
- Other TP characteristics
Leveraging Audit Results

Analytical Models

Closed-Loop Data-Driven Process

Audit Selection

Audits

Data Mining

Texas Audit Select Scoring System

- Designed for Sales Tax audit selection
- Based on a *predictive model* estimating “final tax adjustment”
- Score Scaled between 1 and 1000
- All active sales tax accounts scored yearly
- Score presented in Audit Select application
- In use since mid-2000
What is a Predictive Model?

A representation of some target function that maps a set of input feature to one or more target variables

- **Inputs**: Gross Sales, Deductions, SIC, Prior Audits,…
- **Target**: Final Tax Adjustment, Change vs. No-Change

Predictive models are “trained” using an historical data set, for which the inputs and the target variable are known.

Main Model Inputs

![Diagram showing model inputs and outputs]
Modeling Audit Outcomes

Tax Filings

Employment Data

Historical Audits

Taxpayer Information

Taxpayer Profile at Audit

Audit Outcome ($)

Modeling Tools

Model

Scoring Taxpayers

Tax Filings

Employment Data

Current Taxpayer Profile

Score

0

1000
High Score region (800 to 1000) produce higher than average tax adjustments
Finding New Leads

- Over one third of current taxpayers scoring above 750 had no prior audits

Score Vs. Priority One

- Top 9% scoring audits vs. P1Audits (9% of total)
- Only 36% of top 9% scoring audits were P1 audits
Score-Enhanced P1 Selection Strategy

- Use scores to refine the Priority 1 selection strategy
  - Replace Audits in Region-1 with Audits in Region-3

Score Vs. “Prior Productive”

- Average tax adjustment for PP audits: $17,700 (median $4,100)
- Top-ranking 20% of the audits based on the Score, the average tax adjustment is $27,000 (median $6,500)
Challenges

- Much more difficult to predict “no-change” outcome than outcome scale
- Score relevance/accuracy limited by prior audit selection criteria
  - Selection Bias Problem
- End-user education: selectors need training to gain confidence in the score
- Score does not replace human judgment, it's just a selection tool

Current Developments

- Score combines two predictive models
  - “Audit Likelihood” model: models the selector judgment
  - “Audit Outcome” model: predicts outcome
- High score if:
  - 1) Taxpayer similar to other previously audited taxpayers, and
  - 2) Likely to result in large tax adjustment

![Diagram of the score process](attachment:image.png)
Ongoing and Future Work

- Audit Select Model Enhancement
  - Additional Tax Payer Factors
    - IRS Data, Return amendments, etc.
  - Better Modeling Algorithms
  - Taxpayer Segmentation – Models by Segment

- Franchise Tax Scoring Model
- Enforcement Models
- Tax Affinity – Non-Filers

Summary

- Data mining has great potential in tax compliance:
  - Translates mountains of data into actionable information, predictions and categorization
  - Improves efficiency of resource-intensive tasks, such as auditing
  - Supports decision making and helps uncover more golden needles …
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