DELIVERY OF AN ANALYTICS CAPABILITY

ENSEMBLES AND MODEL DELIVERY FOR TAX COMPLIANCE

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Overview

Revenue Collection

Establishing Capability

Delivering Outcomes

Ongoing Challenges
   Model Deployment
   Big Data: Many Variables
“nothing ... [is] certain, except death and taxes.”
Benjamin Franklin, 1789

“The hardest thing in the world to understand is the income tax.”
attributed to Albert Einstein

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Taxation Records - Historic Data Collection

- **Taxation and Governance**
  Revenue is fundamental to government.

- **Data Collection**
  2500 B.C. Sumerian (Iraq) and Elam (Iran) peoples marked their tax records onto dried mud tablets.

- We still inscribe tax records today — now electronically

- **Data Mining Opportunities**
  Analyse very large collections (20M by 5K) to check tax payer identity, facilitate reporting (lodgement), ensure compliance, pay refunds or collect debts: the four pillars.

Sources [http://www.upenn.edu/almanac/v48/n28/AncientTaxes.html](http://www.upenn.edu/almanac/v48/n28/AncientTaxes.html) [http://www.crystalinks.com/cuneiformtablets.html](http://www.crystalinks.com/cuneiformtablets.html)
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Australian Taxation Office

...continues this “fine tradition”

- Employs 22,000 staff Australia wide
- Role to collect revenue and process refunds

- 12M Individuals, $600B Income, $120B Tax
- 2M Companies..., $2,200B Income, $50B Tax (after expenses)
- GST $46B, Excise $26B, FBT $3B, ... ≈ $350B total income

- Tax payer’s charter:
  
  *Fair but firm; Assume honesty; Protect privacy*

- Service standards — refunds within days ... hours ... seconds?
- Whilst protecting the integrity of the revenue collection
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  Big Data: Many Variables
Creating an Analytics Capability

- Established as a corporate capability in 2004
- Strong support by visionary CEO and senior executives
- Core team of 15 data miners then and now 30 data miners
- Wider team of 150 data analysts throughout the organisation
- Shared technology throughout organisation
- Provide framework for whole of ATO risk management

Every tax return lodged in Australia today is risk assessed by at least one data mining model.

Models delivering benefit:
- Revenue assurance: impact in $ millions
- More efficient targeting: resource and tax payer annoyance
- Better tax payer experience: briefer involvement
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Challenge 1: Analytics as IT

- Traditional IT: Buy software first then buy expertise
c.f. accounting software and accountants

  c.f. data miners as innovative programmers of data
- A culture of multiple tools and dynamic environments
- A culture of sharing algorithms and experiences
- Flexibility in using any technology as and when required
- Not constrained by traditional corporate IT SOE
Lesson: Analyst First

“Analytics is a non-repetitive, exploratory and creative process where the outcome is not known at the start, and only a fraction of efforts are expected to result in success.”

analystfirst.com

- Analytics is not IT and process.
- Focus is not the tools nor the algorithms!
- Focus needs to be with the skills of the people.
- The people who perform, manage, request and envision analytics.
Challenge 2: Missing Technology
Ensembles

Ensemble concept developed in the 80’s

- Multiple Decision Trees (PhD 1987)
- Remains one of the best off-the-shelf technologies: random forests and boosting.
- Not available in the closed source offerings until recently.
- Yet readily available in the open source community.
Lesson: Commodity Platform

A data mining capability need not be expensive.

Build a network of workstations:

- 16 Cores, 64 bit, top CPU speeds
  512GB RAM, 10TB Disk
- Flexible and open source OS
  Ubuntu GNU/Linux
- Open Source data mining tools
  R, Rattle, Weka + SAS, SPSS as rqd
- Open Source does deliver quality

Advert: Strive for open scientific transparency and repeatability – release an R package (or Weka) then it is also available in SAS, SPSS, Netezza, Micro Strategy...
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Challenge 3: Programming Data Analysis

- Exploratory Data Analysis + Mining: R is second to none
- Analytics is about programming with data, and today’s culture is all about GUI - simplified interfaces
- Skills Shortage → Train 150 Data Analysts
- Rattle developed as a stepping stone to transparent and repeatable analytics in R.
A decision tree model is one of the most common data mining models. It is popular because the resulting model is easy to understand. The algorithms use a recursive partitioning approach.

The traditional algorithm is implemented in the rpart package. It is comparable to CART and ID3/C4.

The conditional tree algorithm is implemented in the party package. It builds trees in a conditional inference framework.

Note that the ensemble approaches (boosting and random forests) tend to produce models that exhibit less bias and variance than a single
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Model Deployment

Big Data: Many Variables
High Risk Refunds (HRR) identified prior to issuing of refunds.

- Traditional rules identify too many “high risk” refunds.
- Some tests might identify 100,000 cases each year.
- Sometimes as few as 5% are found to require adjustment.
- Revenue at risk can be very significant (from $10m to $1b).

Data Mining modelling for HRR.

- Has identified numerous characteristics to better target risk (5%)
- More effectively deploy resources on productive cases.
- Avoid non-productive audits.
- Uses decision trees and ensembles (random forests).
Analytics in Action

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Other Successful Projects

- High Risk Refunds – ensembles of trees
- Required to Lodge ($110M) – ensembles of trees
- Assessing Levels of Debt – Propensity/Capacity to Pay
- Optimal Treatment Strategies
- Identity Theft – Outliers, Unusual, Out of Pattern
- International and Tax Havens – Text Mining
- Complex Structures – Network and Link Analysis
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Challenge 4: Model Deployment is IT

- Deliver PMML from SAS into Teradata open standards and interoperability (KDD98)

- Much data mining is **not** “deployed” models are run ad-hoc as required.

- Models “deployed” by conversion
  - SQL: 2 million lines for RF — 20×200×500
  - C: Netezza to score 15M entities in 90 seconds
  - PMML: deployment in e.g. Zementis’ Adapa

- Challenge is that many (hundreds of) models have been developed and many need to be “deployed”
Model Manager - Models in Production

- Running automatically on demand and event driven.
- Requires a professional production environment:
  - models now have life cycles: traditional dev/test/deploy
  - monitoring of model performance:
    - alerts for out-of-spec models
    - daily dashboards
  - 24/7 support of models

- SAS and SPSS provide model management solutions
- Our developing solution using open source tools:
  - R, Python, Shell, Make (scripting)
  - Bazaar (dev/prod version control)
  - Jenkins (continuous integration framework web interface)
  - ...
Challenge 5: Big Data — Many Variables

- Not really too “big” in the ATO
  - 100M transactions
  - 20M entities
  - 5K variables
- Big enough to present some challenges to traditional tools

- The variables are the “big” issue
- Random Forests are good, but could be better!
- Issues when there are many irrelevant variables.
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Subspaced Random Forests

Research with Chinese Academy of Sciences
Shenzhen Institutes of Advanced Technology.

- Random forests are a popular classification method building an ensemble of a single type of decision tree.

- Algorithmically intuitive and simple.

- Aim is for an ensemble of very different decision trees, with each decision tree by itself being a good model of the data it is based on.

- How to increase diversity and individual accuracy?
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Hybrid Random Forests

- Simple Idea: *Build different types of decision trees—different algorithms—for each randomly sampled training dataset and choose the best tree model for each.*

- Tree types considered: C4.5, CART, CHAID
- Further opportunities:
  - HD, EDD, VED (Decision Master)
  - ctree (R/party)

- A series of experiments suggest that the hybrid approach always delivers the best model.
Experimental Results

The hybrid random forest always performs best for this collection of datasets!!!
Another Approach: Weighted Subspaces

- Performance of a random forest is improved by
  - **Strengthening** each tree
  - Reducing **correlation** between each tree

- Problem of large number of variables:
  - Random selection means too many irrelevant variables

- Introduce the concept of weighted subspace random forests
  - Bias the selection of variables toward most important variables
For this collection of experiments the weighted subspace random forest always performs better with many fewer features.
Summary

- Focus on the “Analyst First”
- Commodity hardware and software provide excellent capability
- Sharing algorithms through R packages (rattle, wsrpart, wsrfl)
- Deployment continues to challenge
Resources and References

- Rattle: rattle.togaware.com
- Guides: datamining.togaware.com
- Practise: analystfirst.com
- Book: Data Mining using Rattle/R
- Chapter: Rattle and Other Tales
Thank You