Cleaning Out the Gutter:

Identifying and Eliminating Deadwood from a Sampling Frame Using Trees

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Andrew J. Dau
Gavin R. Corral, Jodie M. Sprague, Linda J. Young
United States Department of Agriculture
National Agricultural Statistics Service
USDA/NASS

USDA NASS

- Over 400 reports annually
  - Census of Agriculture every 5 years
- Reports driven by surveys
- Surveys driven by sampling frames
  - List frame

Maintaining the Sampling Frame

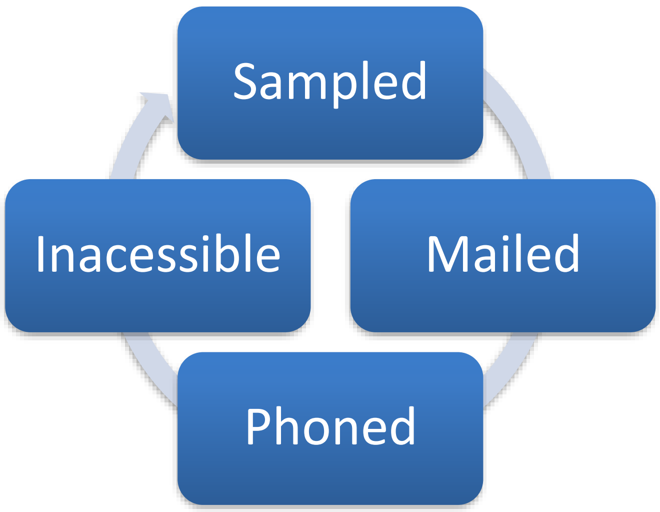
- Processes for adding to frame are on-going.
- Frames age/deteriorate over time.
- Aging records create deadwood.
  - Records that are in business on the frame, but in reality are out of business

Bowling…and “Deadwood”

Source: www.ncaa.com

What's the Problem With Deadwood?

- Impacts on estimates.



- Higher inaccessible rate/ lower overall response rate.
- Can remain on sampling frame for long time.
- Costs → Inflated Samples

How to Identify Deadwood?

- Not easy to predict.
- Despite best efforts, never 100% accurate.
- Can we build a predictive model?
  - 70+ of covariates available

Goal

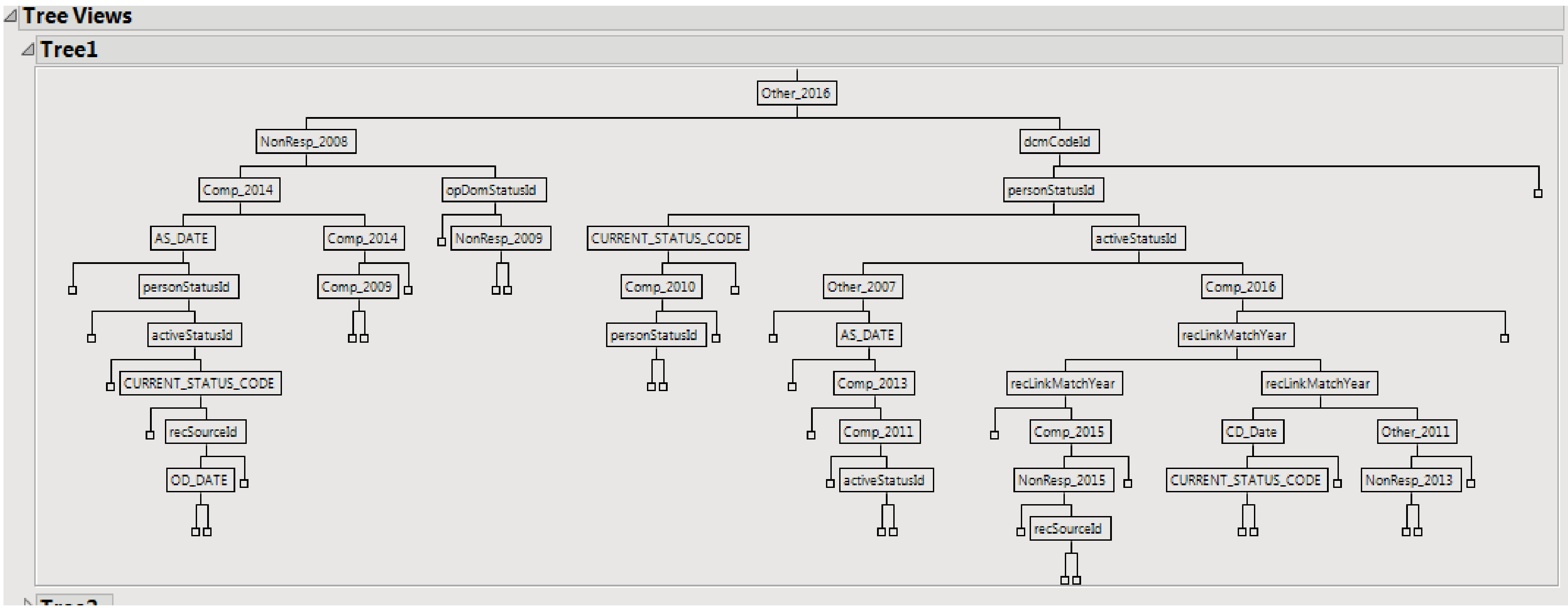
- Build a predictive model which can aid in identifying deadwood thereby maintaining an up-to-date list frame.

Classification and Regression Trees

- "Classification and regression trees are machine-learning methods for constructing prediction models from data." (Loh,2011)

- Boosted Trees - SAS JMP

The Model…An Example



Model Development

- Previous Survey Data
  - What kinds of operations were in-business?
  - What kinds of operations were out-of-business? (deadwood)

- Create binary indicator

- Model Comparison → R^2, ROC, & Confusion Matrix

What's in Our Model?

- Most recent administrative linkage
- Most recent sampling frame data update
- Death Index
- Previous Response History
- Age
- Location
- Ag Census Response

Model Output

- The model creates propensity scores, indicating the likelihood of a record being deadwood.

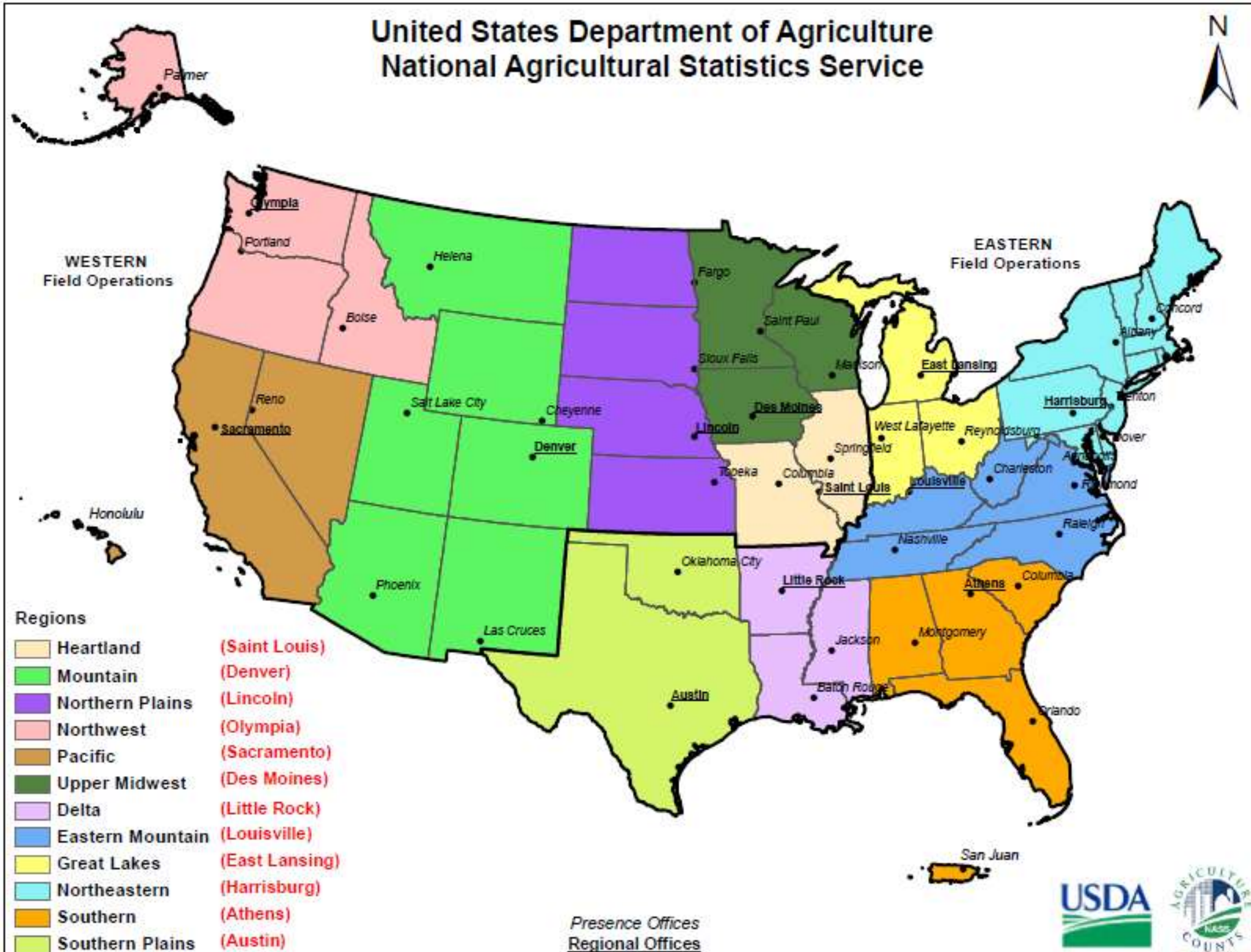
Prob(deadwood= = 1)	Most Likely deadwood
0.0018551978	0
0.0060186538	0
0.9177965625	1
0.00984204	0
0.0114227775	0
0.0018398113	0

The Process

1. Predict likelihood of deadwood for each record in a survey sample.

2. Request face-to-face enumeration during survey process.

3. Verify operating status, complete survey.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Great Lakes (East Lansing)
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September – Acreage, Production, and Stocks Survey (APS)

348 Potential Deadwood Records Identified

4 Regions, Boots on Ground

76 Records

8 Regions, No indication of Deadwood

272 Records

September APS Results

Region	Records	Inaccessible	Deadwood
Targeted 4 Regions	76	21%**	29%**
Non-Targeted 8 Regions	272	39%**	2%**

*Proportions significantly different at .01 level

Are a lot of the inaccessible records in the non-targeted 8 regions actually deadwood?

Small Grain County Estimates Survey (Crops CE)

1098 Potential Deadwood Records Identified

4 Regions, Boots on Ground

356 Records

8 Regions, No indication of Deadwood

742 Records

Small Grain CE Results

Region	Records	Inaccessible	Deadwood
Targeted 4 Regions	356	20%**	38%**
Non-Targeted 8 Regions	742	39%**	18%**

*Proportions significantly different at .01 level

Once again, are a lot of the inaccessible records in the non-targeted 8 regions actually deadwood?

September Recap

- Targeted regions had higher out-of-business (deadwood) rates and lower inaccessible rates.
- All indications point towards expanding the boots on the ground data collection to all 12 regions.

Additional Results

Survey	Year	Deadwood Removed	Deadwood ID'd	Deadwood (%)	Inaccessible (%)
15 Surveys	2016-2018	3,442	8,779	39.21%	25.28%

Conclusion and Future Steps

- The model is accurately identifying a high rate of deadwood records.
- Continue process of identifying potential deadwood at a survey level.
- Approved Decision Memorandum – Jan 24, 2018

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