Ag Internet of Things, Big Data, and the Promise of Open Source for Agriculture

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Today’s Plan

- Context / Background / Farmer Focus
- Three open source projects:
  - Mobile apps for meta data sensing
  - Isoblue / Candroid
  - The Open Ag Data Alliance
- Precision management zone estimation from multi-year yield data
- Observations on the “precision” of yield maps
OATS Group Background

We are farmers:
- North Central Indiana (corn, soy, wheat, cattle)
- NE Colorado, Western Neb. (wheat, corn, millet, beans)
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OATS Group Background

We are engineers:
- Elec. and Comp. / Ag and Bio
- We make open source hardware and software
- We connect widgets to our machines to collect data
Three Open Source Projects

- Mobile apps for meta data sensing
- Isobluue / Candroid
- The Open Ag Data Alliance
Mobile Apps / Autogenic Sensing

Rock
Field Work
Trello Sync
Elevations
Watershed Delineation

Spraying
Planting
Field Notebook
Machinery
OADA Sync

Coming Soon...

Open Ag Toolkit: http://openagtoolkit.org
Real Time Internet of Things: Isoblu3 and CANDroid

ISOBlue Data Flow

Combine

Tractor Bus
- Engine
- Flow sensor

Implement Bus
- GPS

ISOBUS

SocketCAN

ISOBUS Module

Database

ISOBUS

ISOBlue Daemon

Bluetooth

libISOBlue

Android Device

3rd Party App

Cell / WiFi

Cloud

Isoblu3: http://isoblu3.org

Open Ag Technology and Systems
The Open Ag Data Alliance: 
http://openag.io
Ag Data Today: An Example

Prescription Planting Maps

Meet Frank and Andy.
Data Today: An Example

Frank

Yield Data, Soil Tests, Seed Varieties

Rx Map

Local Agronomist
Data Today: An Example

Frank's Combine with OEM A's Monitor

OEM A's Cloud

Yield Data

Yield Data

Frank

Local Agronomist

Yield Data, Soil Tests, Seed Varieties

Rx Map
Data Today: An Example

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OEM A’s Cloud

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Yield Data

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Yield Data, Soil Tests, Seed Varieties

Rx Map

Local Agronomist

Frank

OEM B’s Cloud

Frank’s Combine with OEM B’s Monitor

Open Ag Technology and Systems
Data Today: An Example

Frank's Combine with OEM A's Monitor

OEM A's Cloud

Yield Data

Frank's Computer

Yield Data

Yield Data, Soil Tests

Frank

Local Agronomist

Yield Data, Soil Tests, Seed Varieties

Rx Map

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Yield Data

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Data Today: An Example

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Yield Data, Soil Tests

Fertilizer Co-op

As-Applied Fertilizer Data

Frank

Yield Data, Soil Tests, Seed Varieties

Local Agronomist

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Yield Data

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Data Today: An Example

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Open Ag Technology and Systems
Data Today: An Example

Wait, why do I need data again?
Data Today: An Example

Wait, why do I need data again?
Value Proposition of Data?

A Farmer’s core business is logistics.
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“A key challenge is that, with the exception of Precision Agriculture tools such as auto-steer, telematics, and row shut-offs, the value for many of the products and services have not yet been clearly established.”

-- Digital Transformation of Row-Crop Agriculture, report to Iowa Ag State by the Hale Group, Dec. 2014.
http://www.iowacorn.org/documents/filelibrary/membership/agstate/AgState_Executive_Summary_0A58D2A59DBD3.pdf
Value Proposition of Data?

Obvious Lessons from 20 Years of Fail:

1. It’s really hard to turn data into value.

We still don’t use data for logistics.

Or Evaluation.

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Value Proposition of Data?

Obvious Lessons from 20 Years of Fail:
1. It’s really hard to turn data into value.
2. There is no single “right” solution.
3. No single OEM can provide all data on any given farm.

We still don’t use data for logistics.

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What Farmers Want from Data

Data should flow from whatever source a farmer has into whatever tool a farmer wants without manual intervention.
Data with OADA: An Example

Prescription Planting Maps
OADA Overview

Open Ag Technology and Systems
OADA Overview

Long Live Transferability! --> market picks winners

OADA Is Not a "Cloud"

Tools aren’t tied to storage

Frank’s choice: Frank’s farm, local retailer, Climate, CNH, Winfield, etc.
Frank has complete control over who can see his data.
What Ag / Ag Research Need

Open Source
Volunteers/Industry writing freely available, public code
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>> Much of modern software ....

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What Ag / Ag Research Need

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Open Standards
Standards grow out of implementation, not vice-versa

>> Example: Shapefiles...
What Ag / Ag Research Need

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Standards grow out of implementation, not vice-versa

Market Forces
There doesn’t have to be only one way to do everything
OADA Milestones

Since beginning in March 2014:
CNH/Geosys Demo Finished 12/8/2014
Live Yield Monitor
OADA Milestones

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Valley Irrigation’s ValleyIX certified as OADA v1.0 conformant

The Leader in Precision Irrigation
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Special thanks to our current funding partners!

... and currently 25+ supportive partners around the world!
NEWS RELEASE

August 1, 2016

Open Ag Data Alliance, Servi-Tech launch Real-Time Connections API for weather, soil moisture data

WEST LAFAYETTE, Ind. - The Purdue University-led Open Ag Data Alliance and partner Servi-Tech Inc. announced Monday (Aug. 1) a commercial demonstration of its Real-Time Connections initiative, continuing their mission to help farmers better use data in their daily decisions across all of their operations.
Current Projects: Real Time Connections

Publish formats

OADDA API as base transport

Emphasis on working commercial, real-time system

Can integrate with open source apps / SDKs

For more information:

aaron@openag.io
Current Projects: Trials Tracker

An open source app we’ve been working on at Purdue, designed to work with OADA-conformant cloud providers.
Current Projects: Trials Tracker

- n-serve
  - Area: 35 acres

- fufu dust fungicide
  - Area: 15 acres

- rootworm damage
  - Area: 15 acres
Current Projects: Trials Tracker

Without the cloud you can still:

- Take notes
- Draw areas
- Email shapefiles
- Work offline (cacheable map!)
Current Projects: Trials Tracker

Without the cloud you can still:

- Take notes
- Draw areas
- Email shapefiles
- Work offline (cacheable map!)

But with the cloud you can...
Current Projects: Trials Tracker

But with the cloud you can…

Compare yields
Sync fields
Sync notes with employees/co-op
Load and analyze data FAST
Work offline
Stream live yield from combines
Get polygons from other operations
Current Project: Determine the Management Zones from Multiple Years of Yield Data

- Farm precision management refers to the use of site-specific agronomy for field management zones that respond similarly to similar inputs …

  + Soils, topography, organic material, water holding capacity vary spatially on the scale of a typical field
  + Farmers have ability to target inputs (seed, fertilizer, water) with high spatial resolution

- Goal: Algorithm for determining management zones from multi-year yield data
Current Project: Determine the Management Zones from Multiple Years of Yield Data

- Our data set:
  - North central Indiana (Rochester, IN)
  - About 3,500 acres
  - 7 to 10 years of calibrated yield data
  - Corn, soybean rotation
  - Case IH combines and OEM sensors, monitors

- The state of the art management zone algorithm is called Management Zone Analyst (MZA) – N. R. Kitchen with USDA-ARS Cropping Systems and Water Quality Research Lab, University of Missouri.
Example: Gott East 93

- 7 years of yield data
  - Corn years: 2007, 09, 11, 13
  - Soy years: 2010, 12, 14
- Soil series
- Elevation
- Precipitation
- Growing degree days
Example: Gott East 93

- 7 years of yield data
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- Soil series
- Elevation
- Precipitation
- Growing degree days
Gott East 93: Contours
Gott East 93: Soil Series
"Bb" = Barry loam
"CrA" = Crosier loam, 0 to 2 percent slopes
"Hm" = Houghton muck, drained
"MeB" = Metea loamy sand, 2 to 6 percent slopes
"Mx" = Muskego muck, drained
"Wh" = Washtenaw silt loam
"WkB" = Wawasee fine sandy loam, 2 to 6 percent slopes
"WkC2" = Wawasee fine sandy loam, 6 to 12 percent slopes, eroded
CROSIER SERIES

The Crosier series consists of very deep, somewhat poorly drained soils formed in till on till plains and moraines. They are moderately deep to dense till. Slope ranges from 0 to 4 percent. Mean annual precipitation is about 940 mm (37 inches), and mean annual temperature is about 10.0 degrees C (50 degrees F).

TAXONOMIC CLASS: Fine-loamy, mixed, active, mesic Aeric Epiaqualfs

TYPICAL PEDON: Crosier loam, on a 1 percent slope in a cultivated field at an elevation of 260 meters (852 feet) above mean sea level. (Colors are for moist soil unless otherwise stated.)

Ap--0 to 20 cm (0 to 8 inches); dark grayish brown (10YR 4/2) loam, light brownish gray (10YR 6/2) dry; weak fine granular structure; friable; 1 percent gravel; neutral; abrupt smooth boundary. [15 to 25 cm (6 to 10 inches) thick]

Eg--20 to 28 cm (8 to 11 inches); grayish brown (10YR 5/2) loam; weak medium subangular blocky structure; friable; common medium prominent yellowish brown (10YR 5/6) masses of oxidized iron in the matrix; common distinct light gray (10YR 7/1) clay depletions on faces of peds; 1 percent gravel; slightly acid; clear smooth boundary. [0 to 25 cm (10 inches) thick]
Gott East 93: 4 Years Corn Yield Histograms
Gott East 93: 4 Years Yield Maps

Interpolated Yield 2007 (CORN)

Interpolated Yield 2009 (CORN)

Interpolated Yield 2011 (CORN)

Interpolated Yield 2013 (CORN)
Gott East 93: Yields by Soil Type
GE 93 (corn): does not appear one should manage by soil type alone
Another Model for Management Zone Estimation

- Management zones modeled as Markov random field
  - Labels “hidden”
  - Potts model for spatial relationships
- Multi-year yield vectors modeled as conditionally Gaussian
A. Stochastic Expectation-Maximization

In this approach, we use a stochastic version of an expectation-maximization (EM) algorithm to maximize the probability of the observed yields. This form of conditional independence is a required property of an HMRF. As shown in (7),

\[
\begin{align*}
q^{\theta} & \sim P(X | Y, \theta) \\
& \sim P(X, Y, \theta)
\end{align*}
\]

The yield vectors are assumed conditionally independent of one another, given their respective management zone assignments. It is worth noting these are conditional distributions on the yield, they are not the unconditional distribution. This approach is used instead of EM because, for the model and input data, explicit calculations involving the pmf of an exponential family can make the calculations intractable.

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Algorithm: Stochastic Expectation Maximization (SEM)

- Initialize with fuzzy c-means
- Assume order is known
  - Used: number of soil types + 1
- We compare to MZA algorithm

Fig. 4. High level illustration of the steps of the algorithm. The figure also indicates which of the steps utilize the input yield data. The following sections give more detail on the steps.

1) Sampling (S-Step):
   - Fuzzy C-Means

2) Expectation (E-Step):

3) Maximization (M-Step):
   - Converged?
     - Yes
       - MPM
     - No

4) Refine Parameter Estimates

5) Update Fuzzy C-Means

.initialize Parameter Estimates

Assign Management Zones

Start

Stop
Management Zones: left = SEM, right = MZA (K = 3)
SEM Management Zone
Histograms 2007
SEM Management Zone
Histograms 2009
SEM Management Zone
Histograms 2011
SEM Management Zone
Histograms 2013
Management Zone Estimation: Preliminary Conclusions

- SEM derived management zones appear to cluster according to corn yield potential
- Not as evident in the MZA derived management zones
- Field boundary clearly needs special attention (compaction, yield map errors?)
- The “resolution” that can be achieved is unclear given this data
- Also (but not shown here):
  - Soybeans and corn should be treated separately for purposes of management zone estimation (SEM algorithm can combine them)
  - SEM finds significantly different zones for the two
Where will we go from here?

- Characterize sources of yield mapping errors
  - Models for mass flow, moisture sensor errors
  - Models for grain separation and flow in the combine
  - Couple with combine kinematic model

- Solve inverse problem: From sensor and machine position measurements, attribute the grain to a spot on the field

- Finally: How to design and analyze experiments, using precision farming technologies, which can be used to improve farm management.
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Is this precision attainable?

Where will we go from here?

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Or this?
Where will we go from here?

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**United States Patent**  [19]

**Patent Number:** 5,343,761  
**Date of Patent:** Sep. 6, 1994

**Inventor:** Allen Myers, R.R. 2, Ames, Iowa 50010

**Appl. No.:** 716,293  
**Filed:** Jun. 17, 1991

**Claim:**
METHODOLOGY AND APPARATUS FOR MEASURING GRAIN MASS FLOW RATE IN HARVESTERS

electrical communication with the force measuring apparatus calculates the average value of grain impact force, adjusts this value to compensate for the difference between an actual measured operating speed of the conveyor and a constant reference speed, and calculates grain mass flow rate utilizing a mass flow calibration characteristic which relates grain mass flow rate to average grain impact force, where this calibration characteristic is generated by comparing the average grain impact force, and a grain mass flow rate measured by resolving the force, where this calibration characteristic is generated by comparing the average grain impact force, and a grain mass flow rate measured by resolving the force, and a grain mass flow rate measured by resolving the force.
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Interesting video of mass flow sensor operation on a JD combine:

https://upload.wikimedi...
Where will we go from here?

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A Modern Rotary Threshing Combine Cutaway
Where will we go from here?

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  - Couple with combine kinematic model
Model for Threshing / Separating

Input grain

\[ z^{-1} \]

Grain lost at header

\[ \lambda_{header} \]

\[ 1 - \lambda_{header} \]

\[ z^{-1} \]

\[ 1 - \gamma_{header} \]

\[ z^{-1} \]

\[ 1 - \gamma_{rotor} \]

\[ 1 - \lambda_{rotor} \]

\[ z^{-1} \]

\[ z^{-1} \]

\[ z^{-1} \]

\[ z^{-1} \]

Grain lost out of rotor

\[ \lambda_{rotor} \]

Grain lost out of shoe

\[ \lambda_{shoe} \]

Grain lost out of sieve

\[ \lambda_{sieve} \]

Clean grain

\[ z^{-1} \]

\[ 1 - \gamma_{sieve} \]

\[ 1 - \gamma_{sieve} \]

\[ 1 - \gamma_{sieve} \]

Return (tailings)
Where will we go from here?

- Characterize sources of yield mapping errors
  + Models for mass flow, moisture sensor errors
  + Models for grain separation and flow in the combine
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- Solve inverse problem: From sensor and machine position measurements, attribute the grain to a spot on the field

- Finally: How to design and analyze experiments, using precision farming technologies, which can be used to improve farm management.
Thank you!

Well, even if the big data thing doesn’t work out, we’ll still have auto-steer:
Thank you!

;)