Project Description

1 Introduction

1.1 Overview of Problem

Today it is extremely difficult for researchers or companies in agriculture to use published or unpublished algorithms developed by others; many useful algorithms were written in antiquated coding languages or compiled for long-replaced operating systems. While principles of the algorithms were published in papers, often the code was not and attempts to recreate them are inefficient at best, and likely unsuccessful on average: "unsuccess" is rarely documented. For example, algorithms for soil erosion [1], whole farm modeling [2], watershed delineation [3], and pesticide risk assessment [4] are "locked" in code that is largely inaccessible to and unusable by others in practice. It is tedious and often difficult to tailor them to geo-referenced or high-resolution data which might be available. While these and other tools like them have contributed to the research base in agriculture, few are used in production settings as decision aids; industry has had incomplete access which hinders the pool of new ideas and the ability of industry "on the ground" to provide efficient natural selection of which algorithms provide the best utility and accuracy.

In addition to these issues, the agricultural data industry has begun to suffer (and will soon experience real pain) due to lack of scalability. The industry's software architectures, IT systems, and platforms were all largely developed in an era when a gigabyte (GB) of information was a tremendous amount. Today, a single farm with many power units and implements, replicated soil moisture sensors, irrigation controllers, replicated bin moisture sensors, and many more data sources is realistically capable of producing several terabytes (TB) of data each year. Cloud analytics and storage platforms are not ready for this magnitude of private data – especially as we add imagery from unmanned (air or ground) vehicles which alone can generate on the order of 1 TB per 1,000 acres per season. Additionally, there are countless sites and tools to access public data (e.g., soil type, topography, weather) and these are generally single-use interfaces which generate a particular report. A firm looking to support hundreds or thousands of farms must have systems capable of handling petabytes (PB) of information, possibly distributed between local on-farm storage and in the cloud, while still providing a worthwhile end user experience since individual farms might contribute a data load of 10-50 TB per season. These systems must be more automated; manual handling of data in this magnitude will severely limit data utility to the point of failing to realize even modest potential for agricultural data. Scalable architectures in an agricultural context must be implemented and implemented soon.

This proposal is targeted at approaching these two significant problems jointly: by researching new computing architectures for scalable, distributed agricultural data processing, the goal of having a framework by which future research can be performed, reproduced, and distributed to industry and other researchers can be realized. A future will be possible in which a new researcher can download and use a set of standard, state-of-the-art agricultural algorithms in only a few minutes, directly improving the speed of agricultural innovation. The representative agronomic problem for this project (more details follow) is corn establishment and uniformity. A pilot of methods to work with contextual data to understand this particular issue and improve the outcome should establish a framework to collect and analyze data to find answers to many other issues for corn and other crops such as optimal planting date on various soils and slopes, weed detection via images to compare against a spray threshold and to ascribe an appropriate rate, replanting decisions, and data mining for management zone analysis. A long-term goal is to contribute to the culture of an open-source community in agriculture that can collaborate on the infrastructure for data generation, data analysis, and modeling; an infrastructure that is more amenable to innovation in algorithm refinement and that is truly scalable to the reams of data now available in agriculture is needed. To work toward that community, this project will involve development and dissemination of tools and approaches which address a growing concern to corn growers and researchers and these same tools will have utility beyond corn and the Mid-Western U.S. The three specific objectives for this proposal are: Objective 1: Research microservice-based computing architectures and design a solution for scalable, sharable, real-time agricultural data systems Objective 2: Validate the research of Objective 1 by building an end-to-end solution focused on monitoring stand establishment and early development in corn on the same scalable framework designed in Objective 1, with each solution comprised of reusable microservice components and algorithms Objective 3: Disseminate the algorithms and microservices from Objective 2 as open source projects – so others can use and build upon them with minimal setup time – to demonstrate an infrastructure which catalyzes evolutionary innovation in agriculture.

1.2 Related Body of Knowledge

Recent advances in the digital agriculture landscape are one of the most promising avenues to sustainably achieve increases in global agricultural food production necessary to feed a growing world population. Digital agriculture is a term describing the use of sensors, data, and computational systems to improve and evaluate farming practices for efficiency, sustainability, and increased overall production. It is the means by which innovators will build the systems that feed the world of the future because it is the only means by which the scientific method can be applied to global agriculture at scale.

There are many agricultural researchers around the world trying to improve our collective understanding of the processes and mechanisms which govern food production. They do this by processing data with a host of tools and techniques that range from spreadsheets built from single-experiments to automated machine learning for model development across broad data sets of public and commercial production information. The speed of progress in agricultural innovation is directly correlated to the ability of innovators to both release their work in a way conducive to propagation and commercial implementation and the ability to build upon the work of others with minimal setup time. Increasing the speed of progress is a worthwhile goal and so it is instructive to look at how this has been achieved in the broader technology sector. The innovative culture developed within this sector in the last 10 years has propelled it to more rapid innovative progress than at any prior time in human history. One of the critical features of this improvement has been the realization that innovation is an evolutionary process involving three core functions organized in a feedback loop, as illustrated in Figure 1: mutation, natural selection, and inheritance. In other words, an existing process must be changeable, have a direct path to merit-based survival or death, and retain memory of past attempts to avoid repeating mistakes. The speed of progress is therefore affected by three factors:

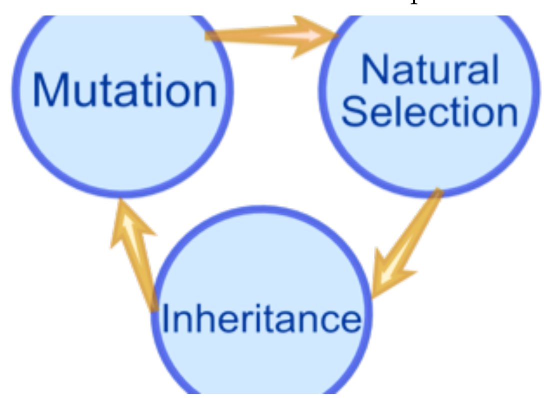


Figure 1: Cycle of evolution towards improved solutions.

- the intelligence with which any particular function can achieve its goal (i.e. how well mutation chooses the next iteration, possibly using statistical tools such as the open source Metric Optimization Engine [5]),
- the speed of transition between functions (e.g. the length of time between natural selection and the next mutation)
- and the parallelization of cycles (i.e. can multiple mutations be attempted simultaneously or must they operate serially)

To speed up innovation, one or more of these factors must be made faster. This approach reduces to three fundamental properties for innovative progress:

- it must be both cheap and fast to try and fail (more mutations),
- it must be possible for bad ideas to be properly identified and abandoned quickly (efficient natural selection),
- and past successes should be easy to incorporate in future innovations (good inheritance).

By adapting the latest in computational architectures which have evolved over the last few years (and their associated communication channels), we propose a framework that should improve all three properties to speed agricultural innovation.

1.2.1 Advances in Computing: Microservices

A "perfect storm" of advances in computing architectures in recent years offers a unique opportunity to address these fundamental issues in the context of agricultural innovation. As the modern software industry has struggled to achieve scalability in exponentially larger volumes of data, traffic, and complexity, some interesting architectural best practices capable of addressing the three properties above have been both tried and proven effective in the demands of commercial use. Primarily, a global community has grown around the idea of microservice-based system design.

Microservices and log-centric architectures [6, 7] are at the center of the computational and communications strategies of many of today's industry leaders in Internet of Things (IoT), social media, cloud computing, and online retailing including LinkedIn, Microsoft, and Amazon. This type of architecture has distinct advantages in performance at large scale while preserving simplicity of software development, revision, and large-scale system management. In this proposal, we plan to leverage its advantages for agricultural data systems and algorithm dissemination strategies.

For purposes of this discussion we define microservices to be small applications with well-defined input and output signals that have a single responsibility within a system [8]. A complete processing platform is composed of many microservices each independently processing the data streams relevant to its task, creating new data streams, and handling specific information requests. Microservice coordination and communications between microservices are handled by distributed consensus servers like Zookeeper or Etc and message broker technologies such as Kafka [9], RabbitMQ, or ZeroMQ. Some of the advantages of microservices relative to traditional monolithic software are:

- It is simple to update microservices or create new ones by starting them and attaching to the live message broker channel.
- Systems based on microservices can easily reallocate resources in response to changing loads by simply adjusting the number of running processes of a particular type.
- Software design is simpler in the microservices architecture because it lends itself to an extremely modular code base. Typical microservices are only a few hundred lines of code [8].

The weakness of the microservices architecture which has been overcome in recent years lies in the communications required to pass messages and data between them. Typically, complete communications between a group of microservices requires a number of service interconnections which is order of the square of the number of services in the group. This centralized management of communications between microservices does not scale well and would be untenable in a large system constantly adding and removing services in response to computational demand.

Until relatively recently message passing schemes such as RabbitMQ, ActiveMQ, and ZeroMQ were used to build well-defined (though rigid) service interconnections. They all provide strong delivery guarantees, which are used to simplify system design since early or ungraceful failure of a particular microservice does not have to result in lost messages. However, to use them in a distributed environment requires complicated consensus algorithms, such as Paxos [10] or Raft [11], and more often than not they become a performance bottleneck.

In turn, microservice systems have begun to embrace truly stateless service designs that operate without regard of other processes in the system, even including other copies of the same service. In general, services should merely react to new data events and information requests in the order they are generated. As a result the message broker could be dramatically simplified to a basic log-like structure, often referred to as an event service bus, that merely stores messages in the order they are received. Kafka [12], LogBus [13], Amazon Kinesis [14], and Azure Event Hub [15], are all examples of highly distributed and highly available implementations of such a log broker. For example, a small and inexpensive three node Kafka cluster is capable of sending and receiving over 2.5 million messages per second and over 249.5 MB of data per second [16]. LinkedIn's production scale Kafka cluster is capable of sending and receiving over 800 billion messages per day which amounts to over 175 terabytes using over 1100 brokers in 60 clusters [17]. This translates to over 63 petabytes per year, precisely the data scales of interest in this proposal.

There are significant challenges to designing a modular system comprised of mostly stateless microservices connected to a high-throughput event bus, including race conditions (near simultaneous events such that the first one completed cannot be communicated quickly enough to the second), unpredictability of message interactions, and many more. Also, many real-world event log-based systems periodically store "snapshots" of state to avoid needing to store an infinite history of messages. We intend to research methods to leverage the strengths of the Open Ag Data Alliance (OADA) project as a means to standardize this state mechanism within the microservice architecture, allowing each microservice to choose its own ideal method of interacting with data: either by querying current state or as a log of changes that results in the current state. This proposal is targeted at researching effective best practices and new paradigms for agriculture-specific problems, and leveraging the features of microservice system design to enable truly shareable algorithms in agriculture.

1.2.2 Advances in Computing: Containers

To complement the appearance of microservice architectures, another recent computing paradigm is transforming the way we think about running and deploying software: containers. Container-based infrastructures are a means of representing an entire running machine (operating system, libraries, and software) in such an efficient way that this representation of a machine can run at native speeds using few extra resources. This "container" representation of a machine ensures that the piece of software will run the same, no matter where or when it is deployed, because it already contains all the details about software library versions, operating system quirks, etc. Note that these containers are a contrast to traditional virtual machines in that they carry little of the storage and computational overhead. For example, a recently popular Node.js-based base container [18] has a total size of only 25MB, yet represents a complete operating system capable of running Javascript processes in Node.

One fundamental problem solved by containers is mitigating the effects of operating system and software library versions changing over time. Even though a particular operating system or software library has fallen into disuse, a container originally built with it can be run just as it was when the original author created it, with negligible performance penalties due to this virtualization.

1.2.3 The Open Source Paradigm

Open source software has radically transformed our world in a very short time. Almost all software and electronic devices in existence today owe at least some part of their function to open source code or hardware. Examples include the Linux kernel, Apple?s OS/X and iOS operating systems, Microsoft's .NET framework, Google's Android operating system, the Apache web server, and the programming language node.js. In fact, as of July 2016, there are over 250,000 open source libraries being downloaded over 1 billion times per week on the popular Javascript code sharing site, Node Package Manager [19].

Open source is the means by which the software industry has moved beyond the limits of what fully proprietary, integrated systems can achieve. Unfortunately, the current scenario in agriculture, both in industry and academia, is ruled largely by closed or incompatible systems and datasets. The key to enabling agriculture to expand the data frontier is the creation of open source communities of developers and researchers that can organically work together, regardless of physical location, on projects and code that have direct interest to the participants.

A paradigm has emerged with best practices for open source projects in the last several years. Code is generally hosted on the free code collaboration site Github, which provides each repository with free web hosting, a project wiki, a powerful issue tracker, and other community management features. We will follow this open source paradigm with the work in this proposal: code and data will be publicly available both during development and after, a mailing list and public Slack channel will be utilized for team communication, and proper documentation will be included with all algorithms as instructions for others to use the code. Links to these resources will be printed in all resulting publications. Tutorials, instructional videos, and a "Getting Started" guide will all be available via a project website.

1.3 On-going and Recent Related Activities

1.3.1 Computing: Open Ag Data Alliance

The Open Ag Data Alliance was introduced in March 2014 by the Purdue Open Ag Technology and Systems (OATS) Group to create an open source common Application Programming Interface (API) for securely and automatically moving data between cloud systems and agricultural applications. At this time OADA has grown to 25 commercial partners on 3 continents. Its technical accomplishments include:

- The definition of a flexible REpresentational State Transfer (REST) API [20]. REST APIs have become the global standard by which data is communicated among most digital systems after its original introduction [21] and subsequent distribution as the core architectural style of the internet.
- A complete open source distributed identity federation [22].
- The demonstration of data exchange over the API between 5 different partners spanning two continents and three countries.
- The creation of an automated conformance test suite in concert with industrial partners seeking OADA conformance certifications.

The project hosts all its code publicly in Github (https://github.com/oada), and maintains an active website at http://openag.io. The group expects several partners to have the first commercially-available OADA-conformant services in place by the end of 2016. The OADA vision is one where, once proper permission is granted, the movement, aggregation, anonymization, and synchronization of data is automatic. For example, a farmer can download a new app for weed management, give the app permission to read his/her herbicide application records on any OADA-conformant cloud, and the app can immediately give recommendations based on past activity. The possibilities are limitless for tools that can exist once there is a standard way to access, synchronize, permission, and semantically understand agricultural data in a distributed context.

1.3.2 Autogenic Metadata Sensing and App Development

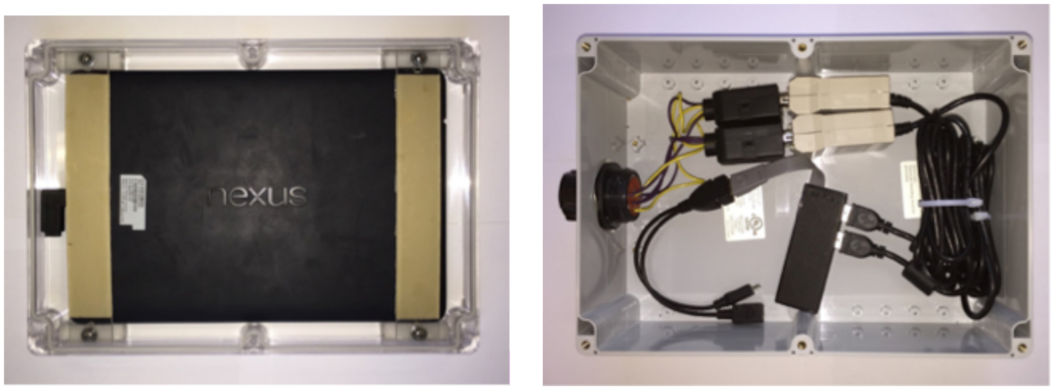
Over the last several years the Purdue OATS research group has been investigating open source software and hardware specifically related to autogenic data – data generated automatically or autonomously with semantic meaning due to context. This was funded in part by a USDA-NIFA grant. A suite of apps were developed and posted on GooglePlay. They facilitate management and logistics by tracking, at the field level, assignments, activities, and progress and have been incorporated into instructional programs and used on research farms [23, 24]. Though the apps were designed primarily for logistics they also facilitate communication and data flow ensuring the capture of context in agricultural research and production settings.

The most recent development with the autogenic project has been a "manure app" [25]. Manure app is indeed autogenic. After set-up and configuration it will autonomously generate complete records of manure application, aggregated at the load level. An inexpensive Bluetooth-enabled ID tag with accelerometers (TI CC265) enables automatic inference of the spreader identity and on/off status. This approach to metadata sensing would be very easily adapted to other agricultural operations such as spraying, planting, tillage, scouting, and even harvest of "batch collected" or baled commodities such as tomatoes, apples, or forages.

1.3.3 ISOBlue and CANDroid: Machine Data to the Cloud for Ag Internet-of-Things

The Purdue OATS group has designed and released the ISOBlue hardware/software package which accesses the Controller Area Network (CAN) bus of an agriculture or forestry machine through a standard diagnostic port. CAN data is streamed to a mobile device through a Bluetooth connection and then can be stored in the cloud [26]. The latest version, dubbed "CANDroid", runs on an Android tablet with only a CAN-to-USB converter (Figure 2). Relevant to this proposal?s focus on microservice architectures, we recently used a Kafka event bus to integrate CANDroid live message streaming into an OADA API for delivery to mobile apps, as shown in Figure 3.

This is an excellent example of the type of architecture described in this proposal. The CANDroid device places each message on the Kafka event bus in the cloud in real-time as it is generated from the machine. This is an example of a "Collector" microservice described in Section 3. A "GPS Parsing" microservice ignores all messages except those containing GPS data, and it transforms the original machine messages into Latitude, Longitude, Altitude, and time, putting a new message back on the bus. A separate "Fuel Rate Parser" microservices does the same. Each of these are examples of "Transformer" microservices described in Section 3. The "Fuel Rate Map Creator" microservice (an example of a "Miner" microservice described in Section 3) watches the bus for GPS and Fuel rate messages with timestamps, and aligns them to create fuel rate map messages composed of a fuel rate at a particular GPS location. Finally, this information is organized into geospatial tiles and put into an OADA server to be available in real-time to any connected mobile devices for analysis and viewing on a map (an example of a "Visualizer" microservice described in section 3). Note that this architecture is scalable and fault tolerant: more data can be handled simply by spinning up more of any particular microservice, and unexpected service failures do not result in cascading overall system failure.



(a) (b)

Figure 2: CANDroid device enclosure's top panel with the (a) Nexus 9 fastened onto the panel and (b) internal USB converters, hub, and power connections.

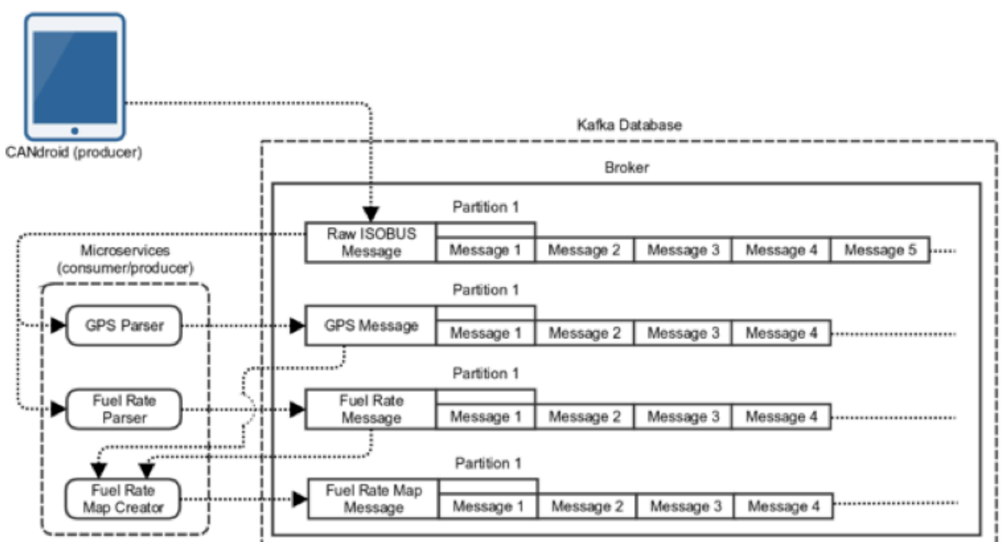


Figure 3: CANDroid microservice-based communications architecture.

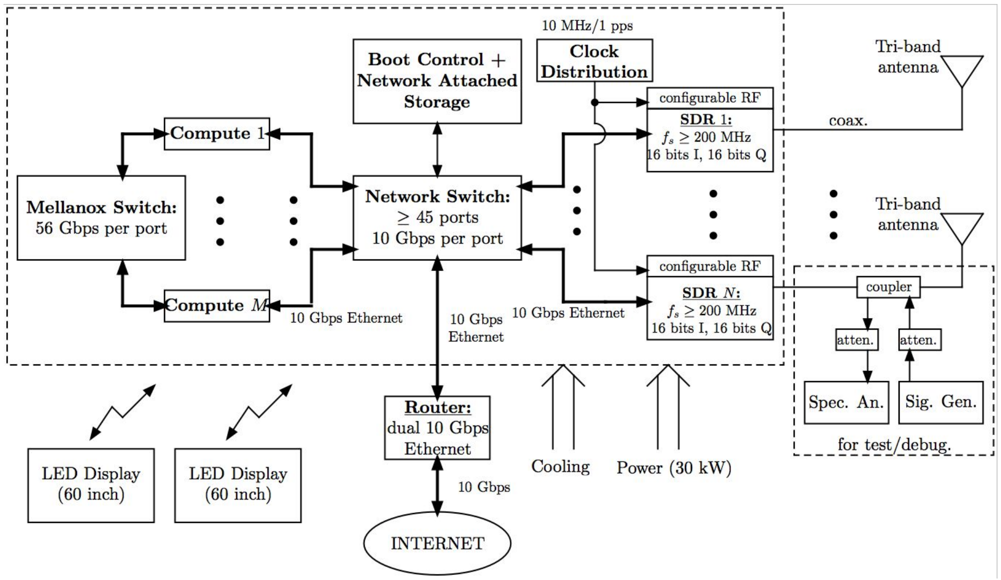


Figure 4: Purdue testbed for multiscale parallel computing.

1.3.4 Parallel Supercomputing Cluster

Members of the proposal team have built a testbed in prior work which is able to exploit the multiple-scale parallelism provided by modern multiple-core general purpose processors, graphics processing units, and FPGAs to leverage modern cloud computing development tools. The testbed represents a cloud supercomputing cluster connected to the analog continuous-time world by high-performance analog-to-digital and digital-to-analog conversion (see Figure 4.) The general purpose servers provide in total 800 cores via hyperthreading. Several TBs of fast (PCIe connected) flash memory is available to the cluster. For purposes of this proposal, this infrastructure will be used to effectively test architectures at scale to determine data throughput, latency and processing requirements and to evaluate fault tolerance.

1.3.5 Computing: Data Visualization

The TrialsTracker app [27] is an open-source mobile application for farmers, agronomists, and other stakeholders to record notes about their on-farm trials which may then be evaluated at the time of harvest. Through a simple note-taking interface, users describe the trial before drawing a polygon of the trial area on the map; they may then tag these trials with their own custom descriptors for categorization of their yield data comparisons. The app can compare yield (or any other data layer) statistics and the differences between two geospatial regions of interest (part of a field compared to the whole field, field 1 compared to field 2, etc.). Rather than the conventional grower-farm-field structure of agricultural field data, data is stored in spatially similar geohash buckets; these geohash buckets streamline the visualization and statistical comparisons as tiles with aggregation appropriate to the zoom level are loaded and displayed according to the applicable geohash level (Figure 5). They also facilitate cross-platform usage of geo-referenced data. With geohashes of differing length driving the tile display, data can be quickly displayed as the user might zoom from a few square meters to several square miles – just like satellite imagery in mapping applications. The data is synced with an OADA server, allowing for real-time data visualization and evaluation of data as it enters the event bus (such as at the time of harvest).

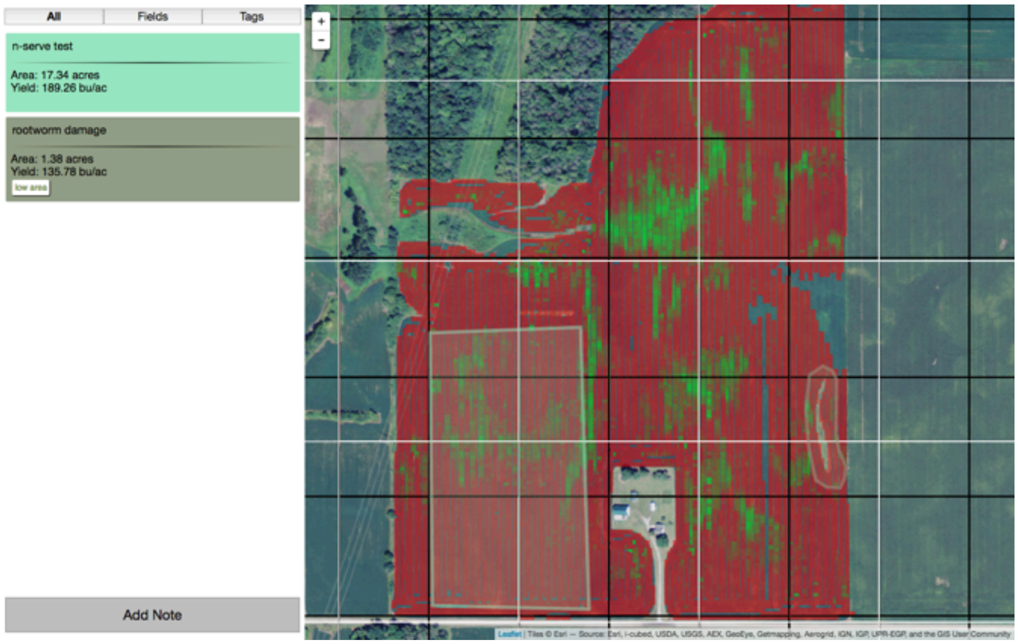


Figure 5: TrialsTracker app (white grids are tiles, black grids are geohash buckets of small chunks of data.

2 Rationale and Significance

2.1 Rationale

The focus of this effort is to leverage current computational approaches to develop and demonstrate an engineered system which can assist in meeting both agronomic and management needs in agricultural research and production agriculture. To seamlessly collect, transform, mine, and visualize agricultural data (both private and public) at large scale will require a major shift in infrastructure. Privacy, security, data quality, and context issues are also important and addressable in the proposed framework, although they are not the focus of this proposal.

2.2 Relationship to Program Area Priorities

This proposal to demonstrate a scalable algorithm sharing framework is a direct application of scientific and mathematical principles to engineer technologies, tool, processes, and systems for it addresses several program area priorities, namely:

- Automation and information systems (with special application to plant production and protection most immediately)
- Develop tools and technologies for monitoring, measurement, and detection in agricultural systems (indirectly by making data from these systems more accessible and interpretable)
- Create a roadmap for the next generation of agricultural technologies, particularly in the areas of cyber-physical systems and information management

2.3 Larger Impacts

Phenomics has gained tremendous traction over the past couple years as a tool for improving plant breeding and genetics. Some have observed, however, that knowledge of physical traits has long been and continues to be a management tool, as well. This project is not solely related to phenotyping, but the framework and infrastructure model will be very applicable as data streams in agriculture increase by orders of magnitude due to imaging and additional sensors.

Greater utility of both public and private data requires easier access and more flexible architectures for collecting, transforming, mining, and visualizing this data. Many of the processes needed can be learned by artificial intelligence systems (neural nets, etc.), but familiarity and access to these tools requires a culture shift toward open-source projects such as this one.

Another larger impact of this proposed work is the improved speed of innovation and refinement with regard to crop production (and other) systems. While one benefit of a microservices framework is improved scalability, it also streamlines innovation and distributed development by isolating large and complex analyses into smaller, more comprehensible and shareable elements. This allows experts to contribute to algorithms, models, and devices with less requisite knowledge than is needed to model ?the whole system?.

3 Approach

3.1 Activities and Sequencing

3.1.1 Objective 1: Research microservice-based computing architectures and design a solution for scalable, sharable, real-time agricultural data systems

The first step will be to formalize the basic architectural components that each microservice can assume are part of the framework in which it is running. Along the lines of typical microservice best practice, each microservice should be capable of learning about and adapting to its environment as a means of improving manageability and reliability. Therefore, a core part of the framework will be the means by which each microservice can achieve this, and corresponding open source code implementing that framework.

The research team has solved similar problems to this in the past as part of their work designing the Open Ag Data Alliance REST API, and many of the same solutions can apply in this context as well. For instance, a client application to an OADA-based cloud service can learn everything it needs about the cloud service by retrieving a cacheable domain configuration document at a standard location, discover the location of resources using the OADA-defined "/bookmarks" endpoint, and later learn the data formats and ontologies used by the cloud via content types that are reported with each resource.

Some of the interesting architectural work here will be around classifying the types of problems, failure modes for those problems that are exploitable for performance gains, and stream-based processing methods for agriculture-specific data systems. Some algorithms which appear straightforward as monolithic applications can become complex when transformed into stateless services that operate on streams of data and make use of the best features of functional programming for parallelizability, reliability, and simplicity.

3.1.2 Validate the research of Objective 1 by building an end-to-end solution focused on monitoring stand establishment and early development in corn...

This phase of the project involves first determining the high-level functions necessary to perform the monitoring of corn plant emergence and early life development, with a focus on scalability using simulated data. This design work will focus on laying out the particular microservices we will need within the framework from 3.1.1, categorized according to the following four classifications:

1. *Microservice Class 1: Collectors.* Collectors are tasked with retrieving external data and placing it into storage locally. Examples of this class include retrieval of soil information,

LiDAR elevation data, NOAA micro rainfall data, and collection of plant health and biomass data from physical sensors.

2. *Microservice Class 2: Transformers.* Given local data on the event bus or stored in an OADA service, convert that data into a different form or index it differently. Examples of this class include transforming NOAA rainfall shapefiles into geospatially-indexed rainfall data, transforming existing LiDAR point cloud data into Digital Elevation Models, reformatting a proprietary binary data files into usable information, etc.

3. *Microservice Class 3: Miners.* Using statistics, models or machine learning, produce insights or aggregates generated from existing data. While it may be difficult to classify a particular algorithm as a Transformer or a Miner given that they both take data as input and produce an output based on that data, Miners differ from Transformers in increased complexity and in the ability to combine multiple sources of data. Examples of Miner microservices include image processing, object recognition, corn growth models, soil erosion models, etc.

4. *Microservice Class 4: Visualizers.* Visualizers may run either as containers which pre-process data to make it suitable for visualization, or as the Javascript code designed to run in browsers or mobile apps and display data to an end user as charts, maps, or animations. Javascript is the most ubiquitous language available, making it an ideal choice for distributable visualization libraries. The main goal of this class of visualizers is to dramatically simplify the work needed by a researcher or developer to look at data generated by the other three classes of microservices. Examples of visualizers include pre-processing raw geospatial data into map tiles, libraries for displaying large amounts of geospatial data on mobile devices, charting tools to display results of basic calculations, and many others.

To adhere to the microservice design philosophy of modularity and fault tolerance, the design of each microservice will require it to operate to the best of its ability in the presence of either partial information or varying granularity of information. For example, a microservice which needs rainfall data as input should be able to give a best-effort output if the input data is a weekly state-wide estimate or if it is a highly-dense on-site network of cloud-connected rain gauges.

The agronomic research topic in this proposal highlights the power of this approach: there are many ways to collect indicators of the various data of interest: canopy height, relative plant height, spacing between plants, physiological development rate, etc. Manual measurement and sampling, drone imagery as available, manned aerial imagery, instrumentation of farm equipment, a hobby-grade radio controlled vehicle with an open source autopilot system, and others are all valid, reasonable means of collecting data. Any particular method that the project team proposes for collecting such information will likely have varying levels of success: some will work well, others will perhaps still require manual sampling and input. The system should be robust enough to produce a result and a confidence metric in such a wide variety of eventual situations, enabling the parallel improvement of any particular type of data collection, processing, or visualization in its own time. This design principle maximizes the chances that a given microservice will be useful in multiple contexts.

3.1.3 Objective 3: Disseminate the algorithms and microservices ...

One of the most critical features of a successful open source project is good documentation that can get newly interested parties up to speed very quickly. Such documentation includes tutorials, getting started guides, blog posts, and videos. The project team intends to explicitly focus on this goal in the second half of the project timeline to minimize the changes necessary to keep documentation up-to-date with rapidly changing code in the early phases of the project, while incorporating other interested developers as early as possible. It is all too easy in normal projects to let the documentation slip in favor of more features, and we intend that this project not fall into that trap by making this an explicit objective.

3.2 Methods

3.2.1 Objective 1: Research microservice-based computing architectures?

Activity 1.1. Architectural research

The team's prior work with the OADA API will be extended to an event bus paradigm creating a similar well-known topic where service discovery can take place. Message types and formats can be communicated via the use of Apache Avro [**?**] as the basic encoding scheme for event bus messages, combined with similar content type structures that already exist within OADA.

In addition to an event bus, each microservice will have access to a local OADA service to retrieve and store information locally that can be shared across microservices. This data store will be assumed by microservices to be eventually consistent in order to remain scalable, and therefore Convergent Replicated Data Types [**?**] will be highly preferred in data models. A microservice that is only interested in events which alter or create some data can use only the event bus, but a microservice that is more interested in processing or querying existing data can rely on the OADA server to retrieve or store the state of some data, either via the REST API directly or by publishing a request on the event bus. A tight coupling between the OADA server and the event bus will enable seamless transition from one to the other by other microservices.

Many other specific architectural details will become necessary as implementation of the framework progresses. These details will be incorporated into the published documentation and publications produced about the architecture. Mechanisms for coordination, best practices for stateless service design, and templates to ease the creation of new types of common microservices will all be important components of this activity.

Activity 1.2. Build a container-based implementation using Docker

Each microservice will be designed to run in a Docker container that can communicate with the OADA service and the event bus. Docker's Compose (Compose, 2016) and Swarm (Swarm, 2016) utilities will be used to build the service interconnections between containers, making any instance of the overall system runnable both locally on a developer's computer and in a cloud provider such as Amazon Web Services (AWS) or Microsoft Azure. The end result is a system of many services that can be very simply installed and started with only two commands: a "git clone" and a "docker-compose start".

Activity 1.3. Test scalability and fault tolerance

The scalability of this system will be evaluated by instrumenting the various components of the system for profiling, and simulating real-time actors producing fake data at realistic rates for thousands of farms. The project team will make use of existing supercomputing infrastructure described in Section 1.3.4 to evaluate the design decisions of this phase of the project in terms of scability, latency, data integrity, and fault tolerance. It will also utilize existing open source microservice testing utilities such as ChaosMonkey (ChaosMonkey, 2016), a microservice designed to randomly stop other microservices in a system in order to evaluate robustness.

3.2.2 Objective 2: Validate the research of Objective 1 by building an end-to-end solution focused on monitoring stand establishment and early development in corn...

Activity 2.1. Construct data collection platform

Outfit an inexpensive, ultra-low ground pressure ground robot with Crop Circle (Holland Scientific, 2011) optical sensors, still and video cameras to generate a rich data stream to test the infrastructure. This imagery and data will be geo-referenced with RTK accuracy; occasional ground-truthing locators will be placed in the field.

Activity 2.2. Architect and build microservice types and their interactions

The project team currently intends to build many if not all of the following microservices for this proposal:

- Collectors:
  - Retrieve SSURGO soil data and load into local OADA server for geospatial regions of choice
  - Retrieve LiDAR elevation data from several of the available public sources
  - Collect data from the roving Crop Circle equipped robot and store in OADA server
- Transformers:
  - Convert SSURGO soil output formats into the proper subset of factors likely to affect germination, emergence and stand establishment
  - Convert optical sensor legacy format data into geospatially-indexed maps
  - Convert optical sensor output to plant population, plant spacing, plant height and NDVI geospatially-indexed maps
- Miners:
  - Process imagery into stand count, physiological stage, or canopy height estimates using a state-of-the-art open source neural network image processing framework such as Caffe (Caffe, 2016)
  - Process image and sensor geo-referenced data to identify key sampling points in a field
  - Process image and sensor data with different wavelength filters to determine which best detect early season NDVI
- Visualizers:
  - Pre-process raw geospatial data into tiles for efficient map display and statistical calculation on mobile devices using the open source algorithms created by the project team for the in-development TrialsTracker open source application (TrialsTracker, 2016)
  - Efficient synchronization and display of real-time geospatial data based on the popular Leaflet.js mapping framework (Leaflet, 2016) (also created by the project team for TrialsTracker application)
  - Charting tools to display results of basic calculations (plant height vs. soil moisture at planting, etc.) using D3.js (D3, 2016) or similar charting libraries
  - Visually show and communicate pre-computed sampling locations on mobile devices while a researcher, agronomist, or or robot ?walks? a field

Activity 2.3. Quantify success of corn plant emergence and stand establishment

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3.2.3 Disseminate the algorithms and microservices ...

Activity 3.1.Code and Project management

The codebase for the project will reside in the Open Ag Toolkit github project (OpenATK, 2016), maintained by the project team as a result of prior USDA funding (GRANT 10867241). Each microservice will have its own repository in that project, complete with issue tracking, documentation, and communication channels for developers. A roadmap for development will be maintained in a new website specific to this project. A mailing list and public Slack team will be created for all developer communication. In this way, both design decisions and the code implementing those decisions will be publicly available from the first day and indefinitely after the project completes.

Activity 3.2 Development of Documentation

The proposal team will produce simple video introductions, written tutorials, and extensive documentation within the codebase in order to maximize the ability of others to learn about the code and contribute to the open source effort. In addition, a website will be maintained for the project in Github Pages.

Activity 3.3 Optimizing Installation and Code Distribution

It is important once the base framework and individual microservices have been developed that the installation procedures be optimized for other researchers not necessarily as well versed in computing as the original developers. The Node Package Manager (npm) (NPM, 2016) provides an excellent demonstration of this within the Javascript community. All Javascript-based code will be released as packages via npm. In addition, all Docker images will be released via the free Docker image sharing service Dockerhub. The single-line commands necessary to install and run each item will be documented, and any areas of installation which appear too complex will be a focus for improvement.

3.3 Expected Outcomes and Deliverables

Aligning with the long-term goal and project objectives, key project outcomes will be a framework for algorithm sharing which incorporates a microservices approach. Design with containers in mind will improve long-term stability of solutions for agriculture and the microservices model should improve the speed at which innovation in agricultural algorithm and data innovation can occur. Specific deliverables will include sample microservices and algorithms, paired with data sets which are available open-source; these will be directly related to corn production since the focus is on establishment and uniformity during early stage growth. This code, however, should be readily adaptable to other uses of similar data whether for field crops, horticultural crops, or any large geo-referenced data sets.

3.4 Evaluation: Analyzing, assessing, and interpreting results...

3.4.1 ? of the microservices

Each microservice will be formally evaluated with the following criteria:

- Robustness to failure of itself and other copies of itself.
- Robustness to failure of other microservices.
- Ability to function with varying resolutions of input information.
- Response latency (i.e. time from input appearance to output messages)
- Additional storage required

3.4.2 ...of the agronomic study

The accuracy of automated methods for the determination of successful stand establishment, such as image analysis tools for quantifying initial plant emergence, stand uniformity, and phenological development rate will be evaluated based on manual measurements. Accurate geo-reference of utility vehicle tracks used to impose emergence delay (with mild compaction) will be compared to emergence and plant stage (at various dates) to validate the identification and location of variation in plant states. The factors affecting measurement accuracy, the amount of time needed and quantity of data generated, and feasibility under diverse field environments will be identified. Some analysis of the gains in confidence earned with larger data sets will be conducted.

3.4.3 ...of the overall framework

The overall framework has two main goals: to be an effective guide for the ag data system designs of the near future, and to be an effective means of algorithm sharing in agriculture. To that end, the overall system will be evaluated according to the following metrics:

- Scalability: theoretical limits on system capacity in terms of data size, latency requirements, network bandwidth, and cost per level of scale in commodity cloud platforms.
- Modularity: each major function of the overall system will be evaluated for dependencies on other parts of the system.
- Learning Curve: the knowledge acquisition necessary to build a single microservice will be described and targeted in tutorials, both for a typical ag-based graduate student level and a computer science graduate student level.

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