Section 3: Week 8: Data Mining IoT

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Data Mining IoT

With ubiquitous access to high-bandwidth wireless networking and cloud computing, physical devices are evolving business capabilities to both monitor and react to changes across their supply chains and operational footprint. These devices produce enormous volumes of unstructured telemetry that require curation processes to transform raw data into business intelligence, enabling data-driven decisions that make the organization more competitive. During this transformation, data mining strategies extract patterns and statistical inferences through regression, clustering, classification, and rule association algorithms (Barua & Mondal, 2019). Each of these algorithmic categories has distinct objectives for scenario-specific applications. Consider the difference between asking (1) how much a customer will spend versus (2) which customers are most alike. Point of sales (PoS) records can answer either question, though the question structure creates a dependency on which sales information becomes relevant facts into (1) regression versus (2) clustering solutions. Using the wrong approach or not defining the outcome goals upfront always leads to nonsensical results (Snee, 2015). Instead, a formal data mining lifecycle begins with a specific question, then collects relevant facts to derive a conclusion. Next, an evaluation method confirms these conclusions are scientifically sound and not wishful thinking through some statistical variance or cross-validation testing. After constructing a probabilistic model of the scenario, the company needs to deploy it into its production environment and begin collecting a return on investment (ROI). Measuring the amount of return depends on Key Performance Indicators (KPI) that typically align with high-level corporate mandates, such as increasing sales per customer or reducing inventory carry times. Despite alignment challenges across data producers, business questions, relevant facts, conclusions, operationalization, and KPIs—planning and methodical approaches lead to success.

# Section I: Business Structure

## Case Study

Black Bean started as a small 'mom and pops restaurant,' and over the last several years, expanded operations to include hundreds of international locations. The company prides itself on delivering consistently high-quality fruit desserts, regionally sourced from local farms. This local approach to supply chain management allows each site to reduce shipping times and ensure the freshest produce. However, decentralization increases the complexity of the corporate offices to gain insights into individual sites and confirm that it meets health and safety standards. The senior leadership addressed these issues by first defining expectation guidelines for middle management. Initially, supervisors would manually collect metrics across the store though this approach was tedious and full of errors. For instance, when the restaurant becomes crowded, the team wholly dedicates to the customer, causing missed readings. Instead, a transition towards automated solutions with IoT devices provides an economical approach to get this data more consistently and reliably. Technologies, such as Arduino and Raspberry PI, allow users to connect specialized sensors to wireless networks for under ten dollars a unit. This capability opens the door for smart restaurants to measure virtually unlimited aspects of the site, such as refrigeration temperatures, humidity sensors, customer counts, and power consumption. After realizing the success of IoT within the eatery, the leadership team began to ask, what about the supply chain? Using Radio Frequency Identifiers (RFID) and Global Positioning System (GPS) sensors allow shipment tracking with fine-grained granularity. Consider scanning an RFID tag on a fruit container as it passes from the farmer, the distribution center, the receiving dock, and finally, the chef—creating an analyzable lifecycle. However, the lifecycle of the desserts does not end here. It continues with the customer scanning their mobile device, creating a point of sales record, and discussing the purchase on social media.

## What types of data artifacts exist

Black Bean relies on a central data lake hosted in the public cloud to store all raw results from the logistical systems, restaurants, mobile apps, and social media impressions. These unstructured artifacts need to go through several iterations of curation as they promote through the corporate data catalog. For instance, the organization manages thousands of temperature sensors that were manufactured by dozens of providers, each with minor differences to the telemetry schema, such as property names, data type encoding, and units (Fahrenheit versus Celsius). After normalizing the sensor values, they can start to connect into semantic models that describe each aspect of the business. These aspects extend beyond inventory management and include scenarios, such as detecting training gaps and safety concerns. Perhaps an employee frequently leaves the meat slicer running unattended or the freezer door ajar—the telemetry contains sufficient information to derive these states. With the capability to predict state comes the ability to remediate, such as killing the meat slicer's power. The predictive capabilities become even more advanced as IoT devices include video recording, and rely on deep learning to discover domain-specific actions. Consider the benefits of being able to analyze every customer's cashier interaction, and then evangelize the more successful traits.

## What business goals use these artifacts

The first and most critical step in any data mining exercise is to determine the question and then discover supporting evidence. Until this action occurs, the business is unlikely to have a successful deliverable and will spend excessive resources investigating irrelevant materials. After clearly articulating the business value, the engineer teams can perform broad filtration of data sources based on their ability to address those questions. During filtration, having a logical framework can improve the search process through partition pruning of the relevant data stores. For instance, if the business operates in Michigan, there is minimal value in exploring Texas-specific data.

* Snee (2015) misconception that lots of data + analysis = magic.
* A recent outbreak of food poisoning at some locations has damaged the brand's image and caused a significant decrease in sales. The leadership team wants to restore consumer confidence by operationalizing their data lake to answer targeted questions about the incident. Which sites are likely to have an outbreak next? Are food handling procedures being followed? Who should promotional material target?
* Cost for carrying inventory and (Viale, 1996)
* Social media intelligence and impact on customer satisfaction (Gioti, Ponis, & Panayiotou, 2018)

# Section II: Collecting and Enhancement

## Preprocessing Data Resources

Countless failed data mining experiments begin with the assumption that pairing large quantities of data with advanced statistical algorithms produces quality insights. The reason this approach does not work is that the algorithms can only apply statistical inference based on the provided data, and cannot derive domain-specific rules. For instance, a missing value for a temperature sensor might indictes a network failure, versus a smart outlet means the associated device is disabled. Depending on the prediction scenario, these missing values could be the most or least important detail, since the algorithm cannot magically discover these internal rules, training data must account for these examples. According to Gibert et al. (2016), most analysts spend nearly 70% of experimentation time cleaning and preparing data.

* Data Catalog as step in lifecycle (Zambetti, Pinto, & Pezzotta, 2019)
* Before analysis can begin, the data analyst needs to normalize the incoming data through an extract-transform-load (ETL) process. This process needs to perform column renaming and reordering, adjusting quantity units, filtering erroneous values, populating missing values, and similar cleanup actions. When analysis does not handle these aspects upfront, it creates a garbage-in/garbage-out scenario. For example, a temperature reading of 55 degrees could be manually entered as 555 degrees, causing later analysis to become skewed.
* After cleaning and schematizing the incoming data, the next analyst needs to determine which aspects are relevant for their data mining objective. Having large amounts of unrelated information does not improve results, and for many scenarios, it only slows down model training times.
* Another critical challenge is handling missing values (Rawal et al., 2017) as they need to be normalized or removed. These decisions become scenarios specific.
* The cleaned data set might need additional enhancements by combining across related information. For instance, the marketing team can use Point Of Sales + Mobile App + seasonal trends to create targeted marketing campaigns

## Required Collection Resources

* Tracking inventory across the supply chain has several human touch points that need to consider. From the *supplier* placing RFID tags on containers to the *workers* at the distribution center that hold these items until needed. *Managers* need to be responsible and accountable for their *staff* to follow the standards and report metrics in a timely and accurate manner. *Local network managers* do not exist, so some *central networking team* would need to work with IoT vendors to support these sensors. *Operations* teams need to monitor for anomalies using models created by the *data analysis team*. The analysis prioritize which aspects to model based on the *business leadership* direction.
* Multiple hardware technologies need to be deployed to monitor from the garden to the customer's review. These technologies include
  + RFID General tags (Balic et al., 2010)
  + Inventory Tracking with RFID (Zhang et al., 2018)
  + Sharing Point of Sales Systems (Croson & K, 2003)
  + Smart Restaurant with IoT (Koubai & Bouyakoub, 2018)
* Future Capacity or needs exist
  + What happens as the number of sensors increases (e.g., instance learning) (Witten, 2011)
  + Stream processing and real-time analysis (Basanta-Val et al., 2017)

## What logical components or assumptions exist

The semantic model represents a logical component of the distribution, food preparation, or customer satisfaction systems. Each model instance represents a state in time snapshot of various interconnected sensors that collectively describe the broader state. For instance, the state of an individual restaurant site might record hourly the number of guests and workers, weather conditions, inventory levels, storage temperatures, and inner atmospheric levels. Independently these data points can only tell part of the story, versus their correlated aggregate structure communicates the detail. Consider knowing that the number of guests was low for a particular hour, and asking is that a concern? If the worker count is also low or there is a hurricane, then perhaps it is expected. Are some of the guests likely to get food poison? If the model knows how many employees are on sick and the storage temperature variability, then a calculatable probability exists. Similarly, the inventory lifecycle is a temporal model where each checkpoint represents a point in time. At each checkpoint, collecting per container features, such as contents, GPS coordinates, time stamps, and storage conditions, allows the business to predict the decay of that produce at higher precision.

Many assumptions come into these models, such they are complete and not malicious. If an employee was negligent with the storage of inventory, they might seek to cover their tracks to avoid retribution from management (e.g., reporting erroneous values). Concept drift occurs when the features of the model no longer align with predictions. This scenario could happen as preparation items move between stations, and relabeling does not occur, causing telemetry signals with the meat-slicer reporting as the toaster. For specific prediction solutions, this inaccurate state could prevent detection and safety alerting, among other undesirable behaviors. Partial mitigation of these issues can occur during the data cleaning phase by including a curation phase to classify and predict the telemetry source. Imagine a smart outlet is reporting the power consumption—a mixer and toaster will have different time graph distributions and thus different signatures (e.g., Jenson-Shannon Divergence).

# Section III: Evaluation Procedures

## What statistical techniques can measure process ROI

* A successful strategy needs to align the business goals to KPI and then deliver data solutions that improve those objectives. (Gonzales & Wareham, 2019) discuss how this becomes more prominent as the organization grows in maturity
* Liyanage et al. (2018) provide a list of KPIs for smart restaurants such as correct products, reducing delays between orders, recommendation accuracies, and the amount of friction bridging into mobile.
* Statistical analysis
  + Snee (2005) points out that by random chance some features are randomly correlated (ala Multicollinearity)
  + Correlation versus Causation
  + Variance and standard deviations

# Section IV: Future Applications

## What data mining strategies can apply to this information

* Time Series analysis with clustering data to form a semantic model and then use spark to process the algorithms (Talei & Benhaddou, 2018)
* LTSM and neural networks (Keras)?
* Using gestures from video - metalearning (Fong et al., 2016)
* Ensemble methods like Netflix (Bell, Koren, & Volinsky, 2007)

# Conclusions

1. Black Bean is a growing multinational organization
   * They have embraced the need for IoT to automate many internal processes
   * Health and Safety, Customer Satisfaction, Inventory Management
   * Collecting for analysis these data points is complex due to the unstructured nature and heterogeneous formats.
2. The organization needs to identify specific KPIs of interest and then determine which relevant facts support their hypothesis. These facts will need to be cleaned, this is 70% of the total data mining. Garbage in/out.
   * After cleaning the data needs to be segmented and structured in such a way that it supports model training. The model produced needs to be scientificially sound and explainable, ideally through a graphical process.
   * Collecting and recording these figures requires numerous personal and hardware resources. Care needs to take place that it does not become corrupt through errorous data entry and similar situations