Section 3: Week 8: Data Mining IoT

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Data Mining IoT

## Abstract

Ubiquitous access to high-bandwidth wireless networking and cloud computing is evolving business capabilities to monitor and react to changes across their supply chains. The ease of deploying IoT devices creates a need to collect and transform enormous volumes of unstructured telemetry into data-driven decision processes. Organizations that can make more informed choices are inherently 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. However, the question structure creates a dependency on which sales information becomes relevant facts into (1) regression versus (2) clustering algorithms. 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 into its production environment and begin collecting a return on investment (ROI). This ROI should promote business goals and initiatives in a measurable way. 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-first 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 began manually collecting metrics across the store though this solution was tedious and full of errors. When the restaurant became crowded, the team wholly dedicates to the customer, causing missed readings. Transitioning towards automated solutions with IoT devices provides an economic mechanism for acquiring 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. Scanning the RFIDs tag on a fruit container occurs as it passes from the farmer, the distribution center, the receiving dock, and finally, the chef—creating an analyzable lifecycle. The lifecycle of the desserts does not end here, continuing 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 stores telemetry results from logistical, restaurant, mobile, and social network systems inside of their data lake solution. 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, 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 interconnect 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. Having the capability to predict these states is the first step towards automated remediation, such as deactivating misfunctioning equipment. The predictive potential of IoT devices will continue to evolve as they transition from simple data points to high-resolution video.

## 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 a business only operates in Michigan, there is minimal value in exploring Texas-specific data. Consider the scenario where the organization wants to execute the most efficient marketing campaign using the least amount of resources. Without proper planning, the business might stumble upon an acceptable deliverable (local maxima). However, they are unlikely to encounter the global maxima. By defining the objective concretely as “increase awareness of their product to minorities and underserved rural populations,” then it becomes possible to rate the quality of supporting evidence. Now that a logical base case exists, the company can review public and private data providers and perform an initial inclusion filter. For instance, governmental census information contains population statistics that describe high-value segments to target physical advertisements.

Businesses with perishable supply chains hold risk in their carrying inventory. If there is too much inventory, then capital is unavailable for other activities, and too little will miss sales opportunities (Viale, 1996). The organization needs to define Specific, Measurable, Attainable, Realistic, and Timely (SMART) optimization objectives. For instance, using inventory tracking and PoS information can funnel into a forecasting model that predicts how many apples the business will need for the next two weeks. As the precision of this model increases, then the amount of excess carry can decrease, and improve sales margins.

# 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 these plans do not work is that the algorithms can only apply statistical inference based on the provided data, and cannot derive domain-specific rules. For example, a missing value for a temperature sensor might indicate a network failure, versus a smart outlet means the associated device is disabled. These missing values could be the most or least important detail, depending on the prediction scenario (Rawal et al., 2017). Since the algorithm cannot magically discover these internal rules, the training data must account for these situations.

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, filtering erroneous values, populating missing values, and similar cleanup actions. Many analysts reportedly spend nearly 70% of the experimentation time cleaning and preparing data (Gibert, Sanchez-Marre, & Izquierdo, 2016). Another common challenge comes from incoming data arriving in different shapes and sizes, and normalization processes need to standardize those values. Some inventory reports express weights in pounds, and others use kilograms. Another property could use an entirely different range scale that does not linearly map between all reports. Until resolving these discrepancies, values across the reports are not directly comparable. After normalization, there can be multiple rounds of using descriptive statistics to discover anomalies and unexpected outliers. When analysis does not handle these aspects upfront, it creates garbage-in/garbage-out scenarios. For example, an erroneous manual entry of 55 degrees could become 555 degrees, skewing the feature mean-value and all derived calculations. During this cleaning process, it is critical to record the applied actions so that the results are reproducible (Zambetti, Pinto, & Pezzotta, 2019). One solution is to have automation scripts that register each transformation with a data catalog and archive into the data lake.

After cleaning and schematizing the incoming data, next, the analyst needs to determine which aspects are relevant for their data mining objective. Having large amounts of unrelated information does not improve results and might only serve to slow down model training times. More curation iterations could exist to provide data set enhancements by joining across related data sources such as PoS, mobile apps, and external aggregation sources (e.g., US Census).

## Required Collection Resources

Tracking inventory across the supply chain has several integration points that blend between cyber and physical systems. Suppliers need to place RFID passive tags on each container and then scan them for the invoice statements. Trucks haul these containers and report their progress through GPS technologies en route to the distribution warehouses. Warehouse employees move the containers into refrigeration units that report both atmospheric conditions and asset tracking within the distribution center. When those items are ready for restaurant consumption, warehouse employees record the specific containers that become shipped. On the receiving end, managers and staff need to unload the ingredients and begin local accounting of health and safety aspects (e.g., temperature controls). Orchestrating this journey requires commodity hardware (e.g., WiFi routers), specialized systems (e.g., IoT sensors), and manual data entry (e.g., pen and paper). Zhang et al. (2018), proposes a resource tracking system that pairs RFID sensors in doorways with Enterprise Resource Management (ERM) to reduce lost inventory scenarios. Automated steps that rely on hardware are inherently more accurate reliable through consistency improvements. However, having vast quantities of dark data does not provide any value, as new insights are not forming. Croson and Donohue (2003) propose that these insights need to be bidirectional, and sharing forecast predictions with suppliers can reduce the bullwhip effect. Supporting this symbiotic relationship requires collection resources also to publish aggregate partner feeds.

Resource collection expands beyond the inventory supply chain and into the restaurant, where IoT technologies can improve numerous aspects of the customer experience. Surveillance technologies can detect and measure (1) how long customers hang out after purchasing and (2) table cleaning cadences. Fong et al. (2016) describe a system for mining custom gestures from video feeds to determine which actions are occurring. Using a similar technology would allow safety systems to detect erroneous behavior and operate as a circuit breaker. For example, if an employee is intoxicated, they should not be permitted to operate heavy machinery, and detecting this state could prevent an accident. These futuristic scenarios are becoming mainstream because of the ubiquitous access to public cloud platforms, such as Amazon SageMaker and Azure Cognitive Services, and their Deep Learning video support. This paradigm shift towards video-centric technologies provides higher contextualized data, but also requires substantially more bandwidth. It will become prohibitively expensive to upload these video streams, and that creates a need for edge computing that performs an initial curation and filtration process (Basanta-Val et al., 2017). For instance, a local stream processor might classify simple actions and then adjust sample rates to meet the safety policy.

## 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 point in time snapshot of various interconnected sensors that collectively describe the broader state. For example, 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 leave and the storage temperature variability, then a calculatable probability exists. Similarly, the inventory lifecycle is a temporal model where each RFID checkpoint represents a point in time. These collections possess per container features, such as contents, GPS coordinates, time stamps, and storage conditions, allows the business to predict the decay of that produce with higher precision.

Many assumptions come into these models around their completeness and being free from malicious tampering. 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 from the meat-slicer to report 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. The distribution of electrical power consumption over time differs between a mixer and a toaster, and that creates a potential device signature for the classification process (e.g., Jenson-Shannon Divergence).

# Section III: Evaluation Procedures

## What statistical techniques can measure process ROI

Successful projects need to expand on business goals and provide measurable value towards the organizational mission. Mature firms can explain their mission in terms of high-level objectives with KPIs that convey the aggregate performance of these aspects (Gonzales & Wareham, 2019). Black Bean has a focus on increasing repeat customer traffic, so they track through the loyalty rewards programs and PoS data guest return rates. After launching a marketing campaign, this metric can assist in evaluating this program’s performance, using an existing shared understanding of impact and value. Snee (2015) warns about multicollinearity and how given enough random variables, some will naturally correlate. External elements, like diet fads and economic recessions, can also dampen the customer’s appetite for discretionary desserts, irrespective of the marketing campaign’s quality. Liyanage et al. (2018) propose that KPIs should be decomposable with child-KPIs acting as supporting evidence. Unlike the external factors, monitoring order latencies, recommendation accuracies, and similar interactions between customers and a site can isolate the interaction to internal controls. When the internal and external metrics are decaying in unison, it confirms the correlation exists, and a quality regression is attributable to internal quality control. Outside correlation, variance analysis can often describe the likelihood of a problem existing. Assume serving a typical order takes five minutes with a couple of minutes variability. Understanding these norms and their standard distribution provides a numeric score to the extent an observation is an outlier and requires further investigation. Third, cross-validation with test data can also measure the accuracy of a system by assessing its performance against real data. If a prediction system can make reliable forecasts towards a business objective, then it has the potential to generate value.

# Section IV: Future Applications

## What data mining techniques can be applied

The four major categories of data mining are regression, classification, association rules, and clustering techniques (Barua & Mondal, 2019). Association rules are patterns that take the form of ‘if X then Y,’ such as a person that buys bread is likely also to purchase butter. Clustering and classification are related strategies that both attempt to group similar items into buckets. The critical difference is that classification knows the bucket labels ahead of time (supervised) while clustering does not (unsupervised). Regression modeling tries to find a mathematical equation that explains the observations.

Numerous implementation-specific permutations of these categories exist though they all follow the same general structure. Gradient Descent Regression and Multilayer Perceptron Regression, two regression algorithms, both take a feature set and attempt to map the values to a continuous numeric range. Either solution supports forecasting the expected number of future guests with data that is similarly structured. Even distinctly different implementations such as Decision Tree Regression, still follow this consistent input and output format. This consistency enables researchers to follow general scenario recipes to produce scenario-specific results, provided sufficient preparation occurs to represent the data domain entirely. These same generalities apply to IoT metric streams, though a few additional curation actions might need to necessary. Harper (2019) warns of predictive analytics on high-volume/low- quality sources as they tend to be noisy and more costly to compute. Instead, stream processing at the edge can perform aggregations and report moving averages and related statistics. After transforming into low-volume/high-quality data points, emit those metrics to central processing systems. When dealing with time-series data, algorithms like Long Short Term Memory (LSTM), assume relationships between sequences of examples (Talei & Benhaddou, 2018). Consider the contrived sequence of 100, 200, 300, *blank*, and how the mind predicts 400. Similarly, LSTM exploits trends of previous values to discover underlying liner patterns.

Bell, Koren, and Volinsky (2007) discourage sophisticated neural network technologies, arguing that their black-box nature is hard to explain, and instead recommend ensemble methods. Their approach combines several simple classification and regression algorithms to create signal confirmation across multiple sources. This method is both powerful and universal, as it leads to meta-learning and derivation of broader domain-specific context. Imagine an autonomous vehicle that relies on a single image analysis process. Then compare that to multiple discrete subsystems that classify the time of day, regression analysis of the road curvature, and incline of the road. The second modular system is easier to maintain and requires fewer resources due to being low-volume/high-quality feature sets.

# Conclusions

Black Bean continues to grow its international business while staying true to the mission of delivering the best desserts using the freshest local produce. Despite the decentralized supply chain model, the corporate office can still ensure quality standards across the brand. This process began with guidelines that now leverage lowcost sensors to automate data collection of critical metrics across the supply chain, smart kitchen, dining experience, and social networks. Even with automation, there are challenges to collect the relevant data as several cyber-physical junctions exist. These junctions span different technology solution providers that expose the necessary telemetry in proprietary formats.

Collecting dark data is more straightforward than unlocking it, as that requires leadership teams to determine KPIs and align business goals with the corporate mission. Once the research objective is determined, analysts spend roughly 70% of their efforts curating training data and ensuring there is full coverage of the data domain. This curation can require multiple iterations as classifiers, regression, and descriptive statistical inference enhances, normalizes, and prunes the examples. After model formation, there needs to be an evaluation of potential return on investment to the organization. If the project addresses business goals that build on the mission, then this is a matter of prediction performance and cost to operate. Performance needs to consider the distinction between correlation and causation, along with standard variance tests.

Many data mining techniques fall into categorical approaches for extracting patterns, such as classification versus clustering. These generalities continue into future IoT solutions. However, the feature dimensionality will increase exponentially both from the volume of deployed sensors deployed and evolution into streaming video. While specific algorithms, like LSTM, exist, one should consider ensembles of simple algorithms instead of complex monoliths. This approach is both adaptive and provides a path through meta-learning to leverage more domain-specific states as part of the prediction.

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