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Deploying High-Throughput, Low-Latency Predictive Models with the Actor Framework

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Abstract

The majority of data science and machine learning tutorials focus on generating models: assembling a dataset; splitting the data into training, validation, and testing subsets; building the model; and demonstrating its generalizability. But when it's time to repeat the analogous steps when using the model in production, issues of high latency or low throughput can arise. To an end user, the cost of too much time spent featurizing raw data and evaluating a model over features can wind up erasing any gains a smarter prediction can offer.

Exposing concurrency in these model-usage steps, and then capitalizing on that concurrency, can improve throughput. This paper describes how the actor framework can be used to bring a predictive model to a real-time setting. Two case-study examples are described: a live deployment built for the freelancing platform Upwork, a simple text classifier with accompanying code for use as an introductory project.

1. The practice of machine learning

Imagine a firm has brought a specialist in machine learning onto a new project. The firm wants a product which can provide a quality prediction about some regular event happening in the course of the firm's business. The specialist is handed a pile of relevant historical data, and asked: Among the new customers seen for the first time today, who's likeliest to be a big spender? Or: of all the credit card transactions processed in the last hour, which are likeliest to be fraudulent? Or: when a customer enters a query into our website's Search tool, what results should we be returning?

The specialist starts with the first of two phases of their project. They have to identify a model that can be expected to fit predictions over both the historical data and in a way that will generalize to new data. The familiar version of the steps involved in supervised learning:

1. Identify raw source data, and break it down into distinct observations of the pattern you're trying to learn and predict.
2. For each raw observation, produce a p-dimensional vector of features and a scalar label.
3. Split this collection into disjoint training, validation, and testing sets.

4. For each candidate model (and/or each of the model's hyperparameters), fit model parameters to the training vectors and labels, and evaluate the goodness of fit by performing prediction of the validation labels given the validation vectors

5. Select the model whose validation-set predictions came closest to the mark. Use it to then make predictions over the test set. Report this test set performance to vouch for the predictive model you've generated and selected.

Note that this first phase doesn't carry an explicit component of *time urgency*. All else equal, a typical specialist will prefer that the full sequence complete in six hours, and six minutes is better still. But if it takes six days instead, nothing *fundamental* to this first phase has been threatened. The task – finding a model that generates acceptably accurate predictions on new data – is accomplished.

The second phase is to actually put the model's capabilities to use. Given new events and observation that need scoring by the model – is this new customer likely to be a big spender? is this credit card legitimate? – the above featurization and scoring routines need to be run. And in this real-world deployment, it's likely that there are also some strict constraints on how long it takes this sequence to run. All predictions go stale, and some use cases need to act on a prediction within milliseconds of the event itself.

There are some cases where these latency constraints aren't binding. The exact same featurization and scoring routines used to generate and validate the model can be re-run fast enough on new data to produce useful predictions. But this paper focuses on the cases where timeliness requirements exclude the use of the same software developed in the first phase as the backbone of the second phase. What can a lone machine learning specialist do to retool their sequence to run in a production environment?

1.1. Moving to production

If the original software, used to generate and validate the predictive model, is suffering from too-low throughput in producing new predictions, one path forward could be to incorporate more concurrent processing. The three steps to prediction (gathering raw materials, featurizing those materials into vectors, scoring the vectors) can transition from a serial sequence to a pipeline.

Figure 1 demonstrates a modification of the scoring task flow, producing predictions of N events in a sequential and a concurrent pattern. This pipeline offers a few advantages. Scores are produced with less delay after the raw material gathering (useful in case the information in that material is at risk of going stale or out of date).

Most importantly, this redesign provides a clear path forward to speed-up in completing all N scoring tasks. If a system can genuinely perform the concurrent tasks in parallel, as a multicore system might, one can easily picture adding "clones" of this pipeline simultaneously processing more and more partitions of the N events.

1.2. Complexity costs

It can be difficult to put together, from scratch, a high-performance concurrent computing system. It's easy to fall into traps of false sharing, deadlocking, and other difficulties. It's

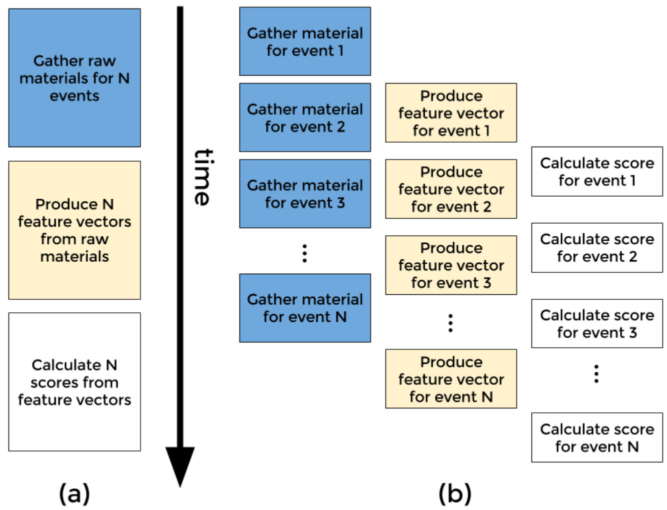


Figure 1: (a) The scoring procedure performed serially. (b) The individual tasks for each event to be scored performed in a concurrent pipeline.

not impossible, but it's definitely tricky and time-consuming, and building a new concurrent system for a single project might fail a cost-to-benefits ratio test.

Fortunately, lots of great work has produced platforms to take this plan to a truly wide scale implementation. Apache Storm (The Apache Software Foundation, 2015b), Apache Spark (especially its Spark Streaming library) (The Apache Software Foundation, 2015a), and Twitter's Heron (Kulkarni et al., 2015) all try to distribute this kind of event-driven computing across multiple machines to ensure the highest possible throughput.

Unfortunately, they're complicated systems. Familiarizing oneself with the API, and managing the underlying infrastructure, requires considerably more expertise above and beyond that of our original model in Figure 1(a). If spreading the load over multiple machines is the only way to meet the required service level of the prediction system, this additional complexity will have to be met with additional resources: maybe the firm will have to start allocating more engineers in addition to more hardware, to what originally was a project of just the single machine learning specialist.

This paper is here to specifically recommend a midpoint between a from-scratch concurrent framework and the mega-scale offerings. The actor framework offers a simple way to reason through concurrent problems, while still being flexible enough to accommodate a variety of approaches to any one problem.

From here, this paper presents a case study where an actor framework was key to bringing a predictive model to production. It interleaves this story with a summary of what an actor framework entails, as well as a description of the framework implementation in the Scala library Akka. It concludes with a reiteration of the advantages (and disadvantages) the actor framework offers and a discussion of why comfort with actors can help machine learning specialists with their work and careers.

2. Case Study: Predicting worker availability at Upwork

Upwork is an online labor platform, connecting freelancers and clients for internet-enabled remote work. There are several patterns for how these work arrangements are struck[1], but one important avenue involves a client using the platform's search engine to discover new freelancers they think would be well suited to the project the client has in mind.

When the client issues a query, e.g., "java developer", "restaurant menu design", "paralegal", they expect to see a result set filled with freelancers with relevant experience who are likely to perform well on a new assignment. The client can then invite any of these freelancers to interview for an open position.[2]

This adds a third requirement to the query's result set: listed freelancers should not only be relevant and high-performing, they should also be receptive to an interview invitation at the time of the query. If the system returns a list of the same ten excellent freelancers for every search for "wordpress template," it's likely that those ten freelancers will wind up deluged with opportunities they're too busy to fill, and for the freelancers ranked just outside that top ten being disproportionately starved for job invitations.

There was an existing heuristic in place to try and capture this, but it was felt a learned model trained on historical data could easily provide higher accuracy.

2.1. Building the predictive model

If the system should only show freelancers available to interview, how should we estimate freelancer availability? This question can be gently reformulated into a question of binary classification: "If Freelancer X were to receive an invitation to interview right now, does their recent use of the site suggest they would accept that invitation, or would they instead reject or ignore it?"

A logistic regression model can help answer this question. Each invitation sent from a client to a freelancer was treated as an example event, labeled as a positive class member if it was accepted and negative otherwise. (There were roughly one million such examples within a relevant and recent time frame.) The goal would be to link the freelancer's recent site activity – within the month prior to receiving the invitation – to the outcome of an acceptance or rejection of the invite.

The raw materials, and derived features, came in four main varieties:

Job application/invitation history In the previous day, how many job applications did Freelancer X create? How many invitations did X receive? How many of each were cancelled by the client, or by the freelancer? How many of each led to filled jobs? Answer these questions again for the time periods: two days, four days, seven days, 14 days, and 30 days.

1. Freelancers can send proposals for a client's publicly posted job opening; groups of freelancers form agencies to share many client workloads; clients and freelancers, already working together outside the platform, moving their relationship onto Upwork to take advantage of the site's payment processing, escrow, or other services
2. Upwork sees the two actions happen in both orders. Sometimes, clients post a job opening, then go searching for freelancers to invite to interview; other times, the client starts by searching and browsing freelancer profiles, and creates the job post once they see someone they'd like to work with.

Hours worked How many hours has Freelancer X billed to any client in the preceding day? two days? ... thirty days?

Server log history In the previous one/two/.../thirty days, how many times has Freelancer X visited pages under the "Job Search," "Message Center," and "View Contractor Profile" sections of Upwork.com?

User profile How many jobs has the freelancer worked in each of Upwork's job categories (e.g., Web Development, Graphic Design, Data Entry)? What is their stated preference for receiving more invitations at this time ("I am available," vs. "I'm not currently available")?

These raw materials (along with a few other sources) could be harvested from three services: a Greenplum relational database for assembling job application and hours-worked data, and an Amazon S3 bucket for the server logs. The user-profile information was an interesting case: the historical state of the profile was logged to a table in Greenplum with each invitation, but a freelancer's present profile state required a call to an internal service's REST API.

Assembling these feature vectors and performing a training-validation-testing split led to a model with a test-set AUC metric of around 0.81. This sufficiently outperformed the existing heuristic's accuracy, and the model was deemed ready for production use. Freelancers would start receiving scores from the model, putting them into buckets of low, medium, and high availability (i.e., high propensity to accept an invitation to interview at this time).

2.2. Throughput constraints in production

An interesting aspect of this modeling task is that hour to hour, any individual freelancer's availability score might swing considerably. Someone who looked dormant three hours ago could decide to log back onto Upwork and start engaging in eager-for-work behavior, sending out job applications and polishing their profile. Another freelancer's behavior might cause a sudden transition from looks-available to looks-overbooked. The more frequently each freelancer could be scored, the more faith Upwork could have that the bucketing used by the search engine was using reliable information. Keeping freshness of the raw material data under four hours was considered a reasonable goal.

Generating those scores meant providing the routine with those four families of raw material. When developing the model using historical data, all four could be gathered and processed in bulk, in advance of the featurization and scoring routines. In a production setting, this remained the case for data from S3 and Greenplum: all that relevant information, for all registered freelancers, could be collected in under an hour.

However, user profiles posed a challenge: given other demands placed on it by other Upwork.com systems, the internal user profile service could only afford to return one user profile every 20 milliseconds to the availability scorer. Any more rapid than that threatened the health of the service. That placed a maximum of 4.3 million scores to be produced per day, one for each up-to-date profile request. With six million total registered freelancers, this put the squeeze on the preliminary goal of every-freelancer, every-four-hours.

2.3. Concurrency under the actor model

A direct re-use of the routines in the model generation software would involve:

1. bulk collection of the job application and worked-hours data,
2. bulk collection of the server log data,
3. bulk collection of as many user profiles as possible before the data from (1) and (2) could be considered stale,
4. featurization and scoring of each freelancer whose profile was collected in step (3).

Steps (1) and (2) combine to a total of about 40 hours of collection and processing time when performed sequentially. Keeping a buffer of 5 minutes aside for Step (4)'s vectorization and scoring (and saving those scores to disc), that means a 4 hour cycle will involve 195 minutes of harvesting user profiles in Step (3). That means an amortized rate of 146,250 scores produced per hour.

The fastest rate possible (one every 20 ms, as limited by the necessary contributions from the user profile service) would mean 180,000 scores per hour. That leaves room for a potential 23% improvement in throughput by moving to a system where user profiles are harvested concurrently alongside the other routines. This potential upside increases as the stringency of the data-freshness guarantee is increased from four hours, to two hours, to one.

2.3.1. The actor model

The actor model makes it easy to architect a concurrent version of the availability system. An actor framework involves three components:

The Actors A collection of objects, each holding a message queue, some private state, and some private methods. This state can only be updated, and these methods can only be called, by the actor object itself, and in response to receiving a message from some other actor. The response an actor takes to each message is fully completed before it begins its response to the next message.

The Messages Simple, immutable objects that contain information or instructions one actor wants another actor to notice.

The Execution Context The harness which ensures that each dispatched message reaches the right actor queue, the computation each actor calls for is completed in order, and that the overall workload is balanced as evenly as possible over the available hardware resources. This system also provides methods for creating new actors, as well as for setting up a timed schedule to dispatch messages at regular intervals to any actor.

This message-passing version of concurrency avoids the race conditions and other difficulties that can arise from many execution tasks sharing mutable state. Anything mutable is isolated inside individual actors, who only share with each other immutable message objects.

The actor model rose to prominence in an artificial intelligence context thanks to work from Hewitt, Bishop, and Stieger. (Hewitt et al., 1973) It's true that compared to classical imperative programming "it imposes a major mind shift in software design." (Korland, 2011) But it's decidedly less intense than the large-scale, distributed alternatives described above, and lets novice or over-worked developers avoid the easy pitfalls of writing one's own stateful multithreading routines.

2.3.2. The concurrent availability system

The family of actors defined for a concurrent availability prediction system uses a hub-and-spoke arrangement, with a single lynchpin actor in charge of featurization from a freelancer's raw data. Three "historian" actors are in charge of polling the higher-bandwidth Greenplum and S3 sources, and another is in charge of (rapidly) polling the user profile service; all four send their findings back to the central featurizer for storage as state variables. A sixth actor receives (freelancer ID, feature vector) pairs from the featurizer, applies the model, and stages these scores to be bulk uploaded back to Greenplum, where the rest of Upwork's freelancer search systems can make use of it.

In more detail:

The featurizer The central hub of the actor system: the featurizer keeps track of each freelancer's worked-hours, job application, and server log information, updating this background data whenever an update is received from a Historian. Whenever a freelancer's information is received from the User Profile Fetcher – that profile holding the final piece of information needed for a complete feature set – the featurizer sends the freelancer's feature vector to the scorer-exporter.

The historians Each is responsible for polling a different kind of raw material resource. The execution context is given a timing schedule for each, and periodically sends them "poll for new data now."

- **Worked-hours historian** Fetches worked-hours records from Greenplum at a schedule of once per hour, forwarding the results found to the featurizer.
- **Job applications historian** Fetches the job application record from Greenplum at a schedule of once per hour, forwarding.
- **S3 historian** Fetches the latest server logs at a schedule of once per hour, forwarding them to the featurizer.
- **User profile fetcher** Every 20 milliseconds, requests and processes user profile data from Upwork's internal service, passing the results back to the featurizer.

The scorer-exporter Waits to receive from the featurizer a freelancer ID, and a vector of features capturing that freelancer's recent use of the Upwork platform. It then applies the (previously trained) logistic regression model to the features, generating a "odds-of-accepting-an-interview-invitation" score for that freelancer. The scorer-exporter stores as many of these as it receives in one hour, then uploads the large collection all at once to a table in Greenplum where it can be read by the rest of the Upwork backend systems and incorporated into search rankings.

This family of actors, along with arrows indicating the principal flow of information from raw material, to feature vector, to availability score, is depicted in Figure 2.

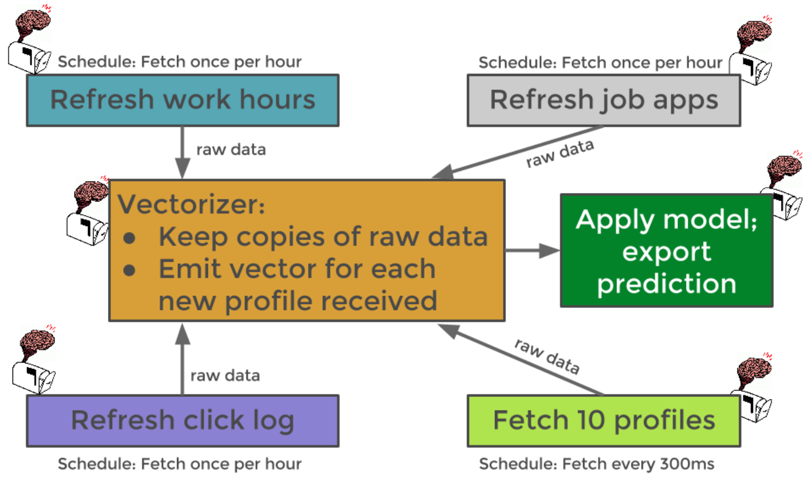


Figure 2: The actor system for freelancer availability scoring. Each actor can be thought of as a mailbox, queuing up messages, with a little brain, holding memories and reacting to those messages one by one.

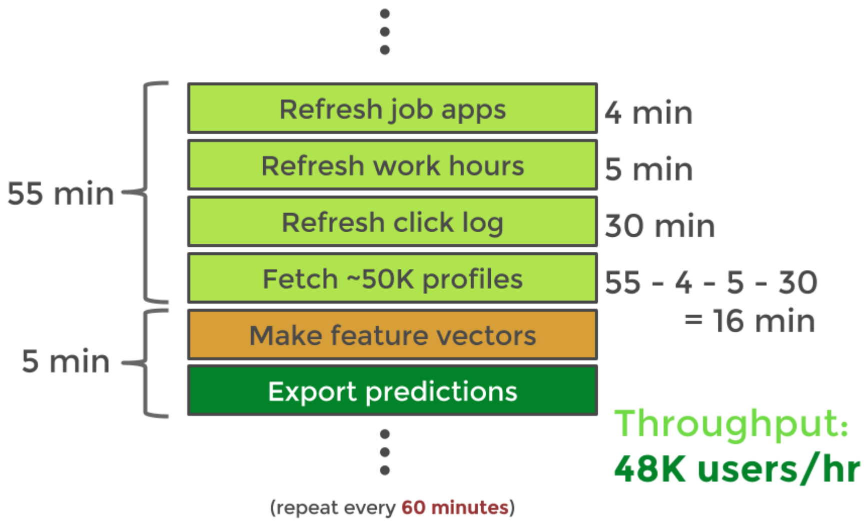
By dividing responsibility for the full scoring pipeline across several distinct workers, the execution context is able to take their concurrent operations and schedule them for the operating system to perform. When the underlying machine offers multiple CPUs, this can mean the actors operate simultaneously, allowing for the latency-reducing speed ups we were hoping for. With single-file processing of messages we avoid problems where, e.g., one step in the scoring procedure tries to read its stored worked-hours data at the same time another step is updating that same data – trying to square this circle from scratch can easily result in code that deadlocks, livelocks, or just plain drops data.

Figure 3(a) depicts the order of operations from our original, sequential scoring system, where raw material gathering, vectorization, and scoring happen one after another, repeating once an hour. Time spent gathering the Greenplum and S3 resources takes away from the rate-limited use of the user profile service.

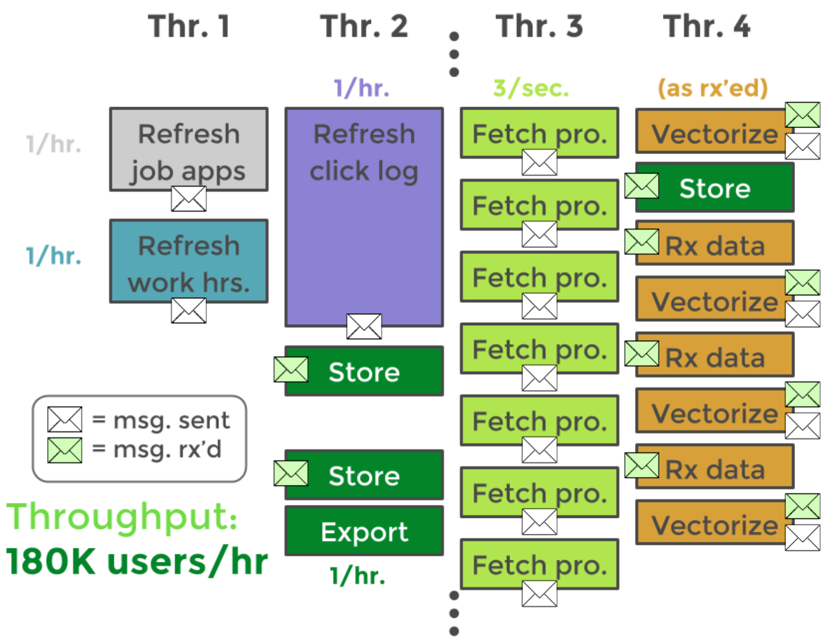
Figure 3(b) demonstrates the concurrent availability scorer run on a four core machine. The execution context is able to provide parallel execution of actor routines, meaning the user profile historian never [3] needs to take a break to let the other raw material harvesters use the execution thread. The rate of availability score production can be maxed out by taking full, round-the-clock advantage of the rate-limited resource.

The actually-implemented availability system, now running as a service on Upwork's backend, achieves this same rate of freelancer score production.

3. This may be a little generous: the Java runtime environment itself may preempt the execution of one or more actor's operations in order to execute services like garbage collection.



(*a*) Sequential operation



(*b*) Parallel operation

Figure 3: The computation cycle for availability in its sequential and concurrent formulations, on a four-CPU system. When data is kept to within one hour of freshness, the actor model provides an approximately 3.75-fold increase in throughput.

3. Case study: a text classification API

As a hands-on demonstration of powering a machine learning service with the actor framework, a repository of code has been put online as a companion to this paper at `https://github.com/bgawalt/papis-akka-demo`. (Gawalt, 2015) The project is an online learner, a text classifier trained one example at a time to distinguish between positive and negative class documents (e.g., spam versus valid messages).

It is implemented in Scala, making use of the Akka library (Typesafe, Inc., 2015) to handle the execution context and actor classes, and the Spray library (The Spray project, 2015) to connect that execution context with HTTP requests from the outside world.

3.1. Scala, Akka, and Spray

Scala is a high level language, designed to allow for easy productivity when developing in both functional programming and object-oriented styles. The Scala language allows developers to define `traits`, ways to partially define class features. Declared attributes can be implemented right along with the `trait` definition itself, or they can defer the implementation until the trait is finally used to build a legitimate `class`.

They're much like Java's `interfaces`, with the added benefit of mixin capabilities – several `traits` can be defined independently with their own methods and fields, then combined arbitrarily to create new subclasses sharing the union of their attributes.

The Akka library provides a `trait` called `Actor`. To define an actor, declare a new `class` which extends `Actor`, which will require you to implement the method `receive`. This method is of type `PartialFunction[Any, Unit]`, exactly as we'd expect: the actor can receive any kind of message, and then does something. The `match` keyword makes it easy to encode reactions to different expected message types, and provide a default "unexpected command" behavior.

Spray then builds on Akka by offering a trait of Actor which can handle HTTP requests and responses in the same asynchronous, message-passing style. It's a convenient way to interact with an actor system.

3.2. Text classification servers

The demo project involves two approaches to the same binary classification task, implemented as two separate API servers: `LoneLearnerServer` and `PackLearnerServer`. These APIs are backed by two types of actor: the request parser and the learner.

The request parser, one per server, inherits from Spray's `HttpServiceActor`, whereby HTTP requests to a particular socket can be forwarded to the parser's `receive` method as a `RequestContext` object. This request context contains useful information, like the URL of the resource requested, and has a `complete` method which should be invoked to send a response to the client via Spray's HTTP mechanisms.

The parser can decode the requested URL and then forward instructions, along with the context to be completed, to the second actor in the system: the learner. Via this API, the learner can perform six tasks: score a new document based on the current model state; update the model state when given a document and a positive or negative class label; report its current state as a string; reset itself to it's original, zero-observations state; synchronize with fellow learners by transmitting information about recently-seen observations, or incorporating that information received from another learner.

The `LoneLearnerServer` has only two actors: one parser, listening to HTTP on a particular socket, and a learner, waiting to receive new documents to judge or labelled documents to learn from. Figure 4 lays out the basic execution flow. There's a risk that too many requests received in rapid succession could cause steadily longer delays between client request and response.[4]

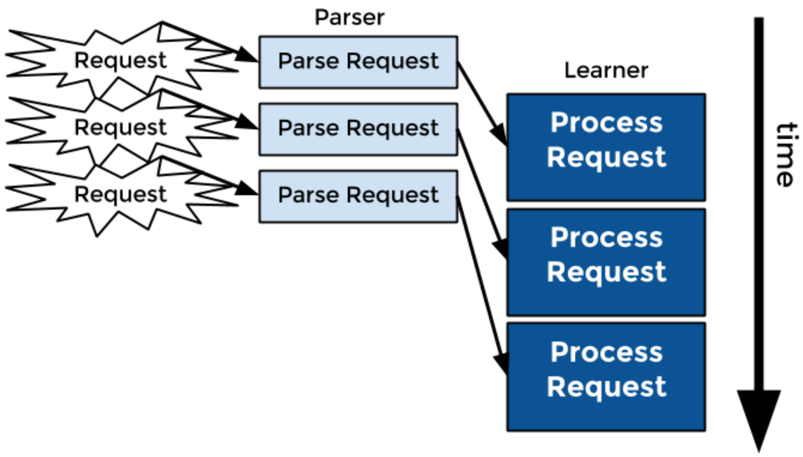


Figure 4: A text classifier system with a lone learner. The learner, with its more computationally intensive tasks, is a potential bottleneck, and latencies can increase as requests pile up.

To break this bottleneck, `PackLearnerServer` has a single parser working with N learner actors. Each HTTP request parsed can be routed to a single learner, selected in a one-after-the-other sequence, or selected pseudorandomly (such as by taking the request's hash value modulo N), spreading the computational load and increasing the odds that the selected learner fielding the request will be unoccupied and ready to work at the time of the request.

The drawback is that when a new labelled document is observed, it can only update the model housed in the selected learner's state. Predictions made by the other learners in the pack won't be able to benefit from the knowledge gained from the update. To patch this, learners are able to send each other update messages after a certain number of observations. This synchronization pulls them offline, unable to respond to new requests until the updates are incorporated.

The machine learning specialist can judge how to trade more frequent updates (and potentially longer delays between request and response) for greater fidelity to the full collection of observed documents. Figure 5 depicts an example of this system's execution of requests.

4. In practice, it seems fairly rapid even with this obvious bottleneck – on a two-core machine, the system was able to process 20,000 predict-then-update cycles in around 60 seconds, or about 1.5 milliseconds per instruction to the learner.

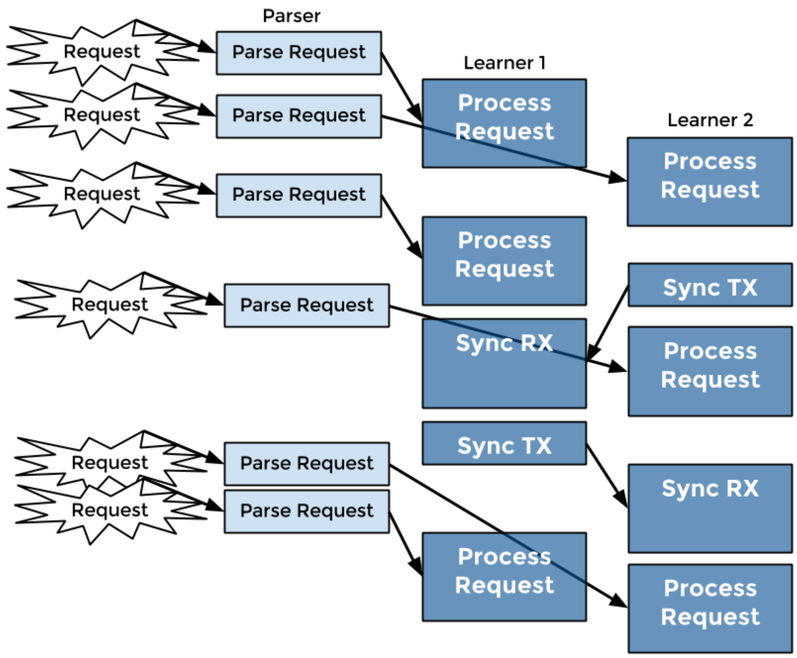


Figure 5: A text classifier system with multiple learners. Request latency can be reduced by sharing the load, though a trade-off has to be made: learners can stay in the dark about recent observations for longer periods (possibly issuing noisier predictions), or more time can be spent synchronizing models between learners (possibly delaying new requests). Note the order in which requests are completed may not match the order in which they were issued.

4. Conclusion

Data science and machine learning are growing as fields and professions, expanding into new domains. That necessarily means engaging firms who find the whole field unfamiliar; and unfamiliarity can inspire risk aversion. These firms in particular are going to greatly appreciate it when a specialist demonstrates a production-ready model at minimal cost, including infrastructure costs, engineering person-hour costs, and maintenance costs.

Exposing concurrency yields efficiencies and reduces costs for any service. Machine learning and data science products benefit especially from the actor framework. It is straightforward to take the standard procedure – gather raw data, produce features from that data, and score those features – and define a collection of actors. That simplicity generates savings in engineering and maintenance efforts.

Upwork was able to take an underperforming sequential software routine, port the particular components to one actor each, and build a system which achieves the maximum possible scoring throughput with much-improved "freshness" guarantees.

The true benefit of the actor framework is its simplicity. The `LoneLearnerServer` text classification API, built on the well-designed Spray and Akka libraries, is under 250 lines of code. And other languages offer their own actor libraries.

For Java, there's the Quasar platform (Parallel Universe Software Co., 2015), as well as a Java API for Akka. For C++, there's CAF, The C++ Actor Framework (Charousset et al., 2014). For Python, Pykka (Jodal, 2015) (though to take advantage of parallelism, your program may benefit from Jython (Python Software Foundation, Corporation for National Research Initiatives, 2015) and it's lack of global interpreter lock). For Ruby, consider Celluloid (Arcieri and Keme, 2015) (as with Python, consider JRuby (Nutter et al., 2015) or Rubinius (Phoenix and Shirai, 2015) to enable thread-level parallelism).

Having the simple version of a predictive API up and running makes it easy to expose and capitalize on greater amounts of concurrency:

- Which actor routines can swap their I/O library for a non-blocking equivalent (freeing thread resources for another actor to use)?
- Can the workload be smoothed by managing duplicate actors (as with `PackLearnerServer` in our example), or by spawning new actors on-demand?
- More ambitiously, can we start building distributed networks of actors, passing info and sharing tasks?

For smaller scale operations, where the actor framework and its concurrency is overkill. Some machine learning applications will need only produce new predictions infrequently enough – a new batch overnight, say – to allow for the exact same routines to be used "in the wild" as were used for designing, validating, and testing the model "in the lab." The machine learning specialist might be of more use moving on to generate a new better model in a new domain, than to rig up a highly concurrent solution.

As the load increases on an actor framework increases, greater care and maintenance is required. Without backpressure, overstuffed mailboxes can cause fatal out-of-memory errors. Timed-out operations need to recover gracefully. As these problems mount, the value proposition of large-scale platforms like Spark and Storm become more compelling.

But for that wide and intermediate range of problems between these scenarios, the actor framework helps the machine learning specialist deliver great results. It is capable enough to support medium-scale applications, especially given the affordability and ubiquity of four, eight, sixteen core systems. It is simple enough that the specialist can assemble the concurrent solution on their own: a production deployment from the same person who designed the model.

Empowered, self-sufficient data scientists are going to continue to push the frontiers of their profession. They should consider adding the actor framework to their toolkit.

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