Resonance: Replacing Software Constants with Context-Aware Models in Real-time Communication

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Abstract

Large software systems tune hundreds of ‘constants’ to optimize their runtime performance. These values are commonly derived through intuition, lab tests, or A/B tests. A ‘one-size-fits-all’ approach is often sub-optimal as the best value depends on runtime context. In this paper, we provide an experimental approach to replace constants with learned contextual functions for Skype- a widely used real-time communication (RTC) application. We present Resonance, a system based on contextual bandits (CB). We describe experiences from three real-world experiments: applying it to the audio, video, and transport components in Skype. We surface a unique and practical challenge of performing machine learning (ML) inference in large software systems written using encapsulation principles. Finally, we open-source FeatureBroker, a library to reduce the friction in adopting ML models in such development environments.

1 Introduction

Hyperparameter tuning of ML models using automation has a very rich literature [9, 2, 18, 8, 10, 17]. However, tuning of application constants such as buffer sizes, thresholds, or timeout settings is commonly done manually. Tuning these constants in live production systems requires overcoming many practical hurdles. In this paper, we study these challenges for a widely used RTC application.

Motivating Example: Consider a video conference call in Skype where one of the participants is using an unstable network. In Skype, if the endpoint stops receiving media packets, the application attempts to “reconnect” the call on an alternate interface (e.g., WiFi interface stops working, but 4G network is active). The reconnect threshold constant represents a careful trade-off. If the switch is triggered too early, the user’s connection is unnecessarily moved into the “call reconnecting” status and starts to renegotiate all call parameters, leading to a false positive (a disruptive experience). If the application waits too long, the user loses patience and hangs up due to frustration. Furthermore, we found mobile users tend to hang up more quickly than desktop users, indicating the contextual nature of this problem as shown in Figure 1.

Literature: Recently, a few solutions and systems have emerged to address some of these challenges. Carbine et al. present SmartChoices, an API to replace heuristics in traditional algorithms with ML models built using standard reinforcement learning (RL) methods [5]. SmartChoices demonstrated the effectiveness on search, sort (pivot index), and cache algorithms. [14] and [11] are examples of applying RL based methods in query optimization and job scheduling systems respectively. To replace runtime constants, we employ a simpler approach of CB as we found it to
scale effectively in our production scenarios compared to RL. This observation has been echoed in [4, 3, 7]. In [3] Bakshy et al. describe Ax, a CB-based optimization and experimentation system for learning parameters at Facebook. In Resonance, we address a novel and practical challenge of ML inference in real-world systems when context information is trapped behind API surfaces.

**Inference Challenges:** Large production software systems comprise of components interacting via strict API boundaries (or contracts). This encapsulation creates isolation, making it difficult to surface context (or features) to be consumed by other components for runtime inference (detailed example in Section 2). A naive approach requires several layers of API changes and alignment that result in the breaking of established contracts. We find that these high development costs were a big driver for the lack of adoption (or integration) of CB models relying on distributed context. It is noteworthy that this challenge is not unique to CB models, but rather any model requiring access to features distributed in siloed components. To scale adoption, we created a library called FeatureBroker that was able to address these challenges and bring down integration costs from 2 months to 2 days.

**Contributions:** This paper makes the following contributions:

- We outline Resonance, an experimental system to replace constants with CB models for RTC scenarios.
- We detail FeatureBroker, a library for managing the conversation between an inference engine and distributed features produced by components. We make this library open source for the benefit of the community [15].
- We present results from applying FeatureBroker to optimize Skype’s audio, video, and transport components in production (Section 3).

### 2 Resonance

**System Overview:** Resonance comprises of the following components: Skype App, A/B test system, Client Inference (CI) and Learning Service (LS) as described in [1]. The benefit of replacing an App constant is evaluated as an A/B test; the control variant represents the fixed constant, whereas the treatment variant is represented by a CB model built using VowpalWabbit (VW) [12] – a well known open source library for CB models. The CI component performs runtime inference based on the App context as specified by the model. The CI component captures training logs comprising of {context value, recommended action, action probability, reward metric} and transmits them to the LS. The LS uses these training logs to produce a VW models (or policies) that get delivered to the client endpoints periodically (e.g., every 4 hours) completing the inference-log-learn loop.

In this paper, we focus our attention on the novel FeatureBroker client library. In our explanations, we define context as a collection of feature values (e.g., network type = WiFi, platform = mobile).

**Feature Broker:** We motivate the need for such a library by way of an example. Consider we want to replace a constant jbHysteresis in the audio component with the output of a CB model. A simple API to do that is shown in Figure 2 (right side).

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2 Figure drawn for illustration by modeling data gathered from real telemetry.
I n f e r e n c e w i t h o u t F e a t u r e B r o k e r

jbHysteresis = model.predict( [ FeatureStore.GetValue("nwType"), FeatureStore.GetValue("platform"), FeatureStore.GetValue("callType") ] );

Figure 2: Left figure shows the organization of components within Skype’s RTC stack; illustrating the distributed nature of features in a well-encapsulated system. The right figure shows the inference performed in the absence of a library like FeatureBroker.

While this API looks simple, practical problems emerge when performing inference using this approach. In this scenario, the context depends on the global state of the system, such as the platform (e.g., desktop/wired), the network type (e.g., wired/WiFi), and call modality (e.g., audio/video). Figure 2 (left side) shows the logical organization of components within our RTC application. While call modality information is available within the audio component, platform and network type information were produced in different components. Moreover, the audio and platform/transport components were separated by many other components and API surfaces. This situation where the features of interest are encapsulated in well-separated components was found to be a common pattern. Component owners want well-defined, stable public API surfaces for maintenance reasons. In addition, expanding them on a feature-by-feature basis is onerous. Furthermore, the components producing the features may not be running in the same thread as the component performing inference, and lastly, the changes in feature values at runtime (e.g., a mid-call change in network type) would require updating the prediction gracefully.

The idea of a simple shared thread-safe key-value feature store proved insufficient for two primary reasons:
1. **Coherence:** Inference libraries need feature values to be stable and consistent. However, as seen above, feature values can update asynchronously (e.g., network type can change mid-call).
2. **Hierarchy:** Features may be consumed by multiple models and inference components. For example, three models (JBHysteresis, ScreenshareEncoding and NetworkReconnect) may consume platform and network type features while having their own local features (e.g., call modality).

The most graceful way to handle this was to make the structure hierarchical and allow it to be “forked” for sub-components.

The shared structure responsible for handling these problems is termed FeatureBroker. It manages the conversation between the client code that provides features (inputs) and consumes inference results (outputs) from a CB model. In this paper, it would be impossible to describe the library in detail. Instead, we highlight the main elements of the solution. Interested readers can see a detailed real-world example in the open-source version of the library FeatureBroker [15]. The key operations of the FeatureBroker are:

1. **Binding Inputs:** Given a name and type returns an “input pipe” into which a feature providing component can feed values.
2. **Associating Models:** Register and describe a scheme for transforming inputs to outputs.
3. **Binding Outputs:** Returns an “output pipe” in which inference consuming models can query for updated values.

The notion of binding draws parallels to binding values for form elements obtained from a database [13]. Finally, it is noteworthy that FeatureBroker can be used with any inference library (e.g., ONNX [16]) and the concept even generalizes beyond CB models - the problem is most amplified in CB inference due to the distributed nature of context generation. As stated earlier, detailed examples are presented in [15].

3 Experimental Results

We present results from three scenarios in Skype. The scenario related to learning the reconnect threshold was described in Section 1. We introduce two other scenarios.

**Scenario: Audio Jitter Buffer (JB) Hysteresis** The JB component absorbs variability in network packet arrivals (i.e., jitter) to present a smooth playout of audio frames transmitted via the network.
JBHysteresis is a meta-parameter controlling the amount of inertia associated with changes in the buffer size. The optimization metric to learn this parameter was Poor-Audio-Rating, an objective metric estimating speech quality based on packet loss, jitter, and conversational delay derived from user ratings [6].

**Scenario: Video Encoding Bitrate Allocation for Screen Share** Screen sharing sessions in VoIP require careful selection of the bitrate. Large bit rates lead to a higher image quality, but are also susceptible to frame freezes due to packet losses under poor network conditions. This quality-distortion tradeoff is characterized by a constant that weights transmission rates and frame freezes. Similar to audio, we optimized for a video technical metric termed Poor-Video-Rating.

**Experiments and Results:** A summary of the experimental data for all three scenarios is presented in Table 1. The data is collected using an $\epsilon$-greedy policy. The $\epsilon$ was set to 0.2 for the experiments. For each experiment, we report the number of unique contexts to convey the range of inputs going into the FeatureBroker. Each of these experiments showed statistically significant improvements between the fixed-constant (default) policy and the model-based policy with a p-value less than 0.01. We note the following:

- These experiments show that we could successfully replace constants with CB models for RTC scenarios. Since these experiments were done in three different components by three different teams, it demonstrates the generality of the FeatureBroker solution.
- New experiments were able to build and re-use the on-boarding of features done by previous experiments. For example, the on-boarding of features for ScreenShareEncoding experiment simplified the integration of the NetworkReconnect model as the two models shared features. Prior to the introduction of FeatureBroker, engineering teams would have to coordinate and align on API changes to expose features. This process would often take multiple days, and has been reduced by an order of magnitude.
- Due to the limited memory and CPU budget in RTC applications, we focused on keeping the footprint of CB models small. The main reason was to scale this methodology so that it can be applied to 100s of scenarios within Skype.

### Table 1: The table captures the overall Summary results from experiments conducted on the representative scenarios.

| Experiment Name          | Audio Jitter Buffer | Screen Share Encoding | Network Reconnect |
|--------------------------|---------------------|-----------------------|-------------------|
| Platforms                | Desktop             | {Desktop, Mobile}     | {Desktop, Mobile} |
| Impressions (Millions)   | 4M                  | 7.6M                  | 19M               |
| RTC Component            | Audio               | Video                 | Transport         |
| Number of Actions        | 10                  | 10                    | 5                 |
| Unique Contexts          | 14                  | 440                   | 390               |
| Metric                   | Poor-Audio-rating   | Poor-Video-rating     | Call Duration (CD)|
| Model Size               | 4 KB                | 22 KB                 | 10 KB             |
| Metric Improvement (%)   | 1.1%                | 9.9%                  | 4.2%              |

In conclusion, we emphasize that the ideas presented in Resonance and challenges solved by FeatureBroker are applicable to many software systems, particularly large codebases that ship with 1000s of system constants.
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