# Learning in situ: a randomized experiment in video streaming

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#### **Abstract**

We describe the results of a randomized controlled trial of video-streaming algorithms for bitrate selection and network prediction. Over the last eight months, we have streamed 14.2 years of video to 56,000 users across the Internet. Sessions are randomized in blinded fashion among algorithms, and client telemetry is recorded for analysis.

We found that in this real-world setting, it is difficult for sophisticated or machine-learned control schemes to outperform a "simple" scheme (buffer-based control), notwithstanding good performance in network emulators or simulators. We performed a statistical analysis and found that the variability and heavy-tailed nature of network and algorithm behavior create hurdles for robust learned algorithms in this area.

We developed an ABR algorithm that robustly outperforms other schemes in practice, by combining classical control with a learned network predictor, trained with supervised learning *in situ* on data from the real deployment environment.

To support further investigation, we are publishing an archive of traces and results each day, and will open our ongoing study to the community. We welcome other researchers to use this platform to develop and validate new algorithms for bitrate selection, network prediction, and congestion control.

## 1 Introduction

Video streaming is the predominant Internet application, making up almost three quarters of all traffic [39]. One key algorithmic question in video streaming is *adaptive bitrate selection*, or ABR, which decides the compression level selected for each "chunk," or segment, of the video. ABR algorithms optimize the user's quality of experience (QoE): more-compressed chunks reduce quality, but larger chunks may stall playback if the client cannot download them in time.

In the academic literature, many recent ABR algorithms use statistical and machine-learning methods [2,23,35,36,38,43], which allow algorithms to consider many input signals and try to perform well for a wide variety of clients. An ABR

decision can depend on recent throughput, client-side buffer occupancy, delay, the experience of clients on similar ISPs or types of connectivity, etc. Machine learning can find patterns in seas of data and is a natural fit for this problem domain.

However, it is a perennial lesson that the performance of learned algorithms depends greatly on the data or environments used to train them. Internet services revolutionized machine learning in part because they have huge, rich datasets. Generally speaking, the machine-learning community has gravitated towards simpler algorithms trained with huge amounts of representative data—these algorithms tend to be more robust in novel scenarios [16,37]—and away from sophisticated algorithms trained on small datasets.

Unfortunately, ML approaches for video streaming and other networking areas are often hampered in their access to good and representative training data. The Internet is complex and diverse, individual nodes only observe a noisy sliver of the system dynamics, and behavior is often heavy-tailed. Accurately simulating or emulating the diversity of Internet paths remains beyond current capabilities [13, 14, 28, 42].

As a result, algorithms trained in emulated environments may not generalize to the Internet [5]. For example, CS2P's gains were more modest over real networks than in simulation [38]. Measurements of Pensieve [23] saw narrower benefits on similar network paths [9] or large-scale streaming services [22]. Other learned algorithms, such as the Remy congestion-control schemes, have also seen inconsistent results on real networks, despite good results in simulation [42].

This paper seeks to answer: what does it take to create a learned ABR algorithm that robustly performs well over the wild Internet? We report the design and findings of Puffer<sup>1</sup>, an ongoing research study that operates a video-streaming website open to the public. Over the past eight months, Puffer has streamed 14.2 years of video to 56,000 distinct users, while recording client telemetry for analysis (current load is about 50 stream-days of data per day). Puffer randomly assigns each session to one of a set of ABR algorithms; users

<sup>&</sup>lt;sup>1</sup>https://puffer.stanford.edu

are blinded to the assignment. We find:

In our real-world setting, sophisticated algorithms based on control theory [43] or reinforcement learning [23] did not outperform simple buffer-based control [17]. We found that more-sophisticated algorithms do not necessarily beat simpler, older algorithms. The newer algorithms were developed using collections of traces that may not have captured enough of the variability or heavy tails we see in practice.

Statistical margins of error in quantifying algorithm performance are considerable. Prior work on ABR algorithms has claimed benefits of 10–15% [43], 3.2–14% [38], or 12–25% [23], based on traces or real-world experiments lasting hours or days. However, we found that the empirical variability and heavy tails of throughput evolution and rebuffering create statistical margins of uncertainty that make it challenging to detect real effects of this magnitude. Even with a *year* of accumulated experience (or representative traces) per scheme, a 20% improvement in rebuffering ratio would be statistically indistinguishable, i.e., below the threshold of detection with 95% confidence. These uncertainties affect the design space of machine-learning approaches that can practically be deployed in this setting [11,24].

It is possible to robustly outperform existing schemes by combining classical control with an ML predictor trained in situ on real data. We describe Fugu, a data-driven ABR algorithm that combines several techniques. Fugu is based on MPC (model-predictive control) [43], a classical control policy, but replaces its throughput predictor with a deep neural network trained using supervised learning on data recorded "in situ," meaning from Fugu's actual deployment environment, Puffer. The predictor has some uncommon features: it predicts transmission time given a proposed chunk's filesize (vs. estimating throughput), it outputs a probability distribution (vs. a point estimate), and it considers low-level congestion-control statistics among its input signals. Each of these techniques has been explored before, but Fugu combines them in a new way. Ablation studies (Section 4.2) find each of these techniques to be necessary to Fugu's performance.

In a rigorous controlled experiment during most of 2019, Fugu outperformed existing techniques—including the simple algorithm—in stall ratio (with one exception), video quality, and the variability of video quality (Fig. 1). The improvements were significant both statistically and, perhaps, practically: users who were randomly assigned to Fugu (in blinded fashion) chose to continue streaming for 10–20% longer, on average, than users assigned to the other ABR algorithms<sup>2</sup>.

Our results suggest that, as in other domains, good and representative training is the key distinguishing feature required for robust performance of learned ABR algorithms. The simplest way to obtain representative training data is to learn *in* 

Results of primary experiment (Jan. 19-Aug. 7 & Aug. 30-Sept. 12, 2019)

Algorithm	Time stalled (lower is better)	Mean SSIM (higher is better)	SSIM variation (lower is better)	Mean duration (time on site)
Fugu	0.12%	16.9 dB	0.68 dB	32.6 min
MPC-HM [43]	0.25%	16.8 dB	0.72 dB	27.9 min
BBA [17]	0.19%	16.8 dB	1.03 dB	29.6 min
Pensieve [23]	0.17%	16.5 dB	0.97 dB	28.5 min
RobustMPC-HM	0.10%	16.2 dB	0.90 dB	27.4 min

**Figure 1:** In a seven-month randomized controlled trial with blinded assignment, the Fugu scheme outperformed other ABR algorithms. The primary analysis includes 458,801 streams played by 44,907 client IP addresses (8.5 client-years in total). Uncertainties are shown in Figures 8 and 10.

situ, on real data from the actual deployment environment, assuming the scheme can be trained on observed data and the deployment is widely enough used to exercise a broad range of scenarios. The approach we describe here is only a step in this direction, but we believe Puffer's results suggest that machine-learned networking systems will benefit by addressing the challenge of "how will we get enough representative scenarios for training—what is enough, and how do we keep them representative over time?" as a first-class consideration.

We intend to operate Puffer as an "open research" project for the next several years. We invite the research community to train and test new algorithms on randomized subsets of its traffic, gaining feedback on real-world performance with quantified uncertainty. Along with this paper, we are publishing an archive of traces and results back to the beginning of 2019, with new traces and results posted daily.

In the next few sections, we discuss the background and related work on this problem (§2), the design of our blinded randomized experiment (§3) and the Fugu algorithm (§4), with experimental results in Section 5, and a discussion of results and limitations in Section 6. In the appendices, we provide a standardized diagram of the experimental flow for the primary analysis and describe the format and quantity of data we are releasing alongside this paper.

## 2 Background and Related Work

The basic problem of adaptive video streaming has been the subject of much academic work; for a good overview, we refer the reader to Yin et al. [43]. We briefly outline the problem here. A service wishes to serve a pre-recorded or live video stream to a broad array of clients over the Internet. Each client's connection has a different and unpredictable time-varying performance. Because there are many clients, it is not feasible for the service to adjust the encoder configuration in real time to accommodate any one client.

Instead, the service encodes the video into a handful of alternative compressed versions. Each represents the original video but at a different quality, target bitrate, or resolution.

 $<sup>^2</sup>$ This effect was statistically significant but driven solely by users streaming more than 2.5 hours of video; we do not fully understand it.

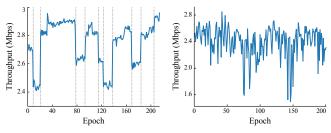
Client sessions choose from this limited menu. The service encodes the different versions in a way that allows clients to switch midstream as necessary: it divides the video into *chunks*, typically 2–6 seconds each, and encodes each version of each chunk independently, so it can be decoded without access to any other chunks. This gives clients the opportunity to switch between different versions at each chunk boundary. The different alternatives are generally referred to as different "bitrates," although streaming services today generally use "variable bitrate" (VBR) encoding [29], where within each alternative stream, the chunks vary in compressed size [44].

Choosing which chunks to fetch. Algorithms that select which alternative version of each chunk to fetch and play, given uncertain future throughput, are known as adaptive bitrate (ABR) schemes. These schemes fetch chunks, accumulating them in a playback buffer, while playing the video at the same time. The playhead advances and drains the buffer at a steady rate, 1 s/s, but chunks arrive at irregular intervals dictated by the varying network throughput and the compressed size of each chunk. If the buffer underflows, playback must stall while the client "rebuffers": fetching more chunks before resuming playback. The goal of an ABR algorithm is typically framed as choosing the optimal sequence of chunks to fetch or replace [35], given recent experience and guesses about the future, to minimize startup time and presence of stalls, maximize the quality of chunks played back, and minimize variation in quality over time (especially abrupt changes in quality). The importance tradeoff for these factors is captured in a QoE metric; several studies have calibrated QoE metrics against human behavior or opinion [4, 10, 19].

Adaptive bitrate selection. Researchers have produced a literature of ABR schemes, including "rate-based" approaches that focus on matching the video bitrate to the network throughput [18,21,25], "buffer-based" algorithms that steer the duration of the playback buffer [17,35,36], and control-theoretic schemes that try to maximize expected QoE over a receding horizon, given the upcoming chunk sizes and a prediction of the future throughput.

Model Predictive Control (MPC), FastMPC, and Robust-MPC [43] fall into the last category. They comprise two modules: a *throughput predictor* that informs a predictive *model* of what will happen to the buffer occupancy and QoE in the near future, depending on which chunks it fetches, with what quality and sizes. MPC uses the model to plan a sequence of chunks over a limited horizon (e.g., the next 5–8 chunks) to maximize the expected QoE. We implemented MPC and RobustMPC for Puffer, using the same predictor as the paper: the harmonic mean of the last five throughput samples.

CS2P [38] and Oboe-tuned RobustMPC [2] are related to MPC; they constitute better throughput predictors that inform the same control strategy (MPC). These throughput predictors were trained on real datasets that recorded the evolution of throughput over time within a session; CS2P clusters users by



(a) CS2P example session (Figure 4a from [38])

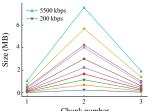
**(b)** Typical Puffer session with similar mean throughput

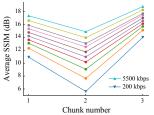
**Figure 2:** Puffer has not observed CS2P's discrete throughput states. (Epochs are 6 seconds in both plots.)

similarity and models their evolving throughput as a Markovian process with a small number of discrete states; Oboe uses a similar model to detect when the network path has changed state. In our dataset, we have not observed CS2P and Oboe's observation of discrete throughput states (Figure 2).

Fugu fits in this same category of algorithms. It also uses MPC as the control strategy, informed by a network predictor trained on real data. This component, which we call the Transmission Time Predictor (TTP), incorporates a number of features, none of which can claim novelty on its own. The TTP is not a "throughput" predictor per se; it predicts the transmission time of a proposed chunk with a given filesize. That observed throughput varies with filesize is a well-known effect [5,29,44], although to our knowledge Fugu is the first to use this fact operationally as part of a control policy. Fugu's predictor is also probabilistic—it outputs not a single predicted transmission time, but a probability distribution on possible outcomes. The use of probabilistic or stochastic uncertainty in model predictive control has a long history [33]. but to our knowledge Fugu is the first to use stochastic MPC in this context. Finally, Fugu's predictor is a neural network, which lets it consider an array of diverse signals that relate to transmission time, including raw congestion-control statistics from the sender-side TCP implementation [15, 40]. We found that several of these signals (RTT, delivery\_rate, FlightSize) benefit ABR decisions (§5).

Pensieve [23] is an ABR scheme also based on a deep neural network. Unlike Fugu, Pensieve uses the neural network not simply to make predictions but to make *decisions* about which chunks to send. This affects the type of learning used to train the algorithm. While CS2P and Fugu's TTP can be trained with *supervised learning* (to predict chunk transmission times recorded from past data), it takes more than "data" to train a scheme that makes decisions; these schemes need training *environments* that respond to a series of decisions and judge their consequences. This is known as "reinforcement learning." Generally speaking, reinforcement learning techniques need to be able to observe a detectable difference in performance by slightly varying a control action; this requires large amounts of training, and systems that are challenging to





- (a) VBR encoding lets chunk size vary within a stream [44].
- **(b)** Picture quality also varies with VBR encoding [29].

**Figure 3:** Variations in picture quality and chunk size within each stream suggest a benefit from choosing chunks based on SSIM and size, rather than average bitrate (legend).

simulate faithfully or that have too much variability present difficulties [11,24]. The authors of Pensieve recently tested a similar scheme on video traffic at Facebook [22], observing a 1.6% increase in bitrate in a large real-world test.

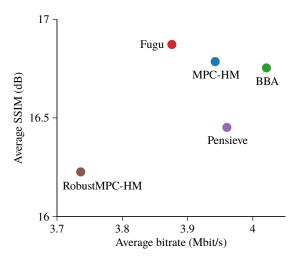
# 3 Puffer: an ongoing live study of ABR

To understand the challenges of video streaming and measure the behavior of ABR schemes, we built Puffer, a free, publicly accessible website that live-streams six over-the-air commercial television channels. Puffer operates as a randomized controlled trial; sessions are randomly assigned to one of a set of ABR or congestion-control schemes. The study participants include any member of the public who wishes to participate. Users are blinded to algorithm assignment, and we record client telemetry on video quality and playback. Our Institutional Review Board determined that Puffer does not constitute human subjects research.

Our reasoning for streaming live television was to collect data from enough participants and network paths to draw robust conclusions about the performance of algorithms for ABR control and network prediction. Live television is an evergreen source of popular content that had not been broadly available for free on the Internet. Our study benefits, in part, from a law that allows nonprofit organizations to retransmit over-the-air television signals without charge [1]. Here, we describe details of the system, experiment, and analysis.

# 3.1 Back-end: decoding, encoding, SSIM

Puffer receives six television channels using a VHF/UHF antenna and an ATSC demodulator, which outputs MPEG-2 transport streams in UDP. We wrote software to decode a stream to chunks of raw decoded video and audio, maintaining synchronization (by inserting black fields or silence) in the event of lost transport-stream packets on either substream. Video chunks are 2.002 seconds long, reflecting the 1/1001 factor for NTSC frame rates. Audio chunks are 4.8



**Figure 4:** On Puffer, schemes that maximize average SSIM (MPC-HM, RobustMPC-HM, and Fugu) delivered higher quality video per byte sent, vs. those that maximize bitrate directly (Pensieve) or the SSIM of each chunk (BBA).

seconds long. Video is de-interlaced with ffmpeg to produce a "canonical" 1080p60 or 720p60 source for compression.

Puffer encodes each video chunk in ten different H.264 versions, using libx264 in veryfast mode. The encodings range from 240p60 video with constant rate factor (CRF) of 26 (about 200 kbps) to 1080p60 video with CRF of 20 (about 5,500 kbps). Audio chunks are encoded in the Opus format.

Puffer then uses ffmpeg to calculate each encoded chunk's SSIM [41], a measure of video quality, relative to the canonical source. This information is used by the objective function of BBA, MPC, RobustMPC, and Fugu, and for our evaluation. In practice, the relationship between bitrate and quality varies chunk-by-chunk (Figure 3), and users cannot perceive compressed chunk sizes directly—only what is shown on the screen. Our results indicate that schemes that maximize bitrate directly do not reap a commensurate benefit in picture quality (Figure 4).

Encoding six channels in ten versions each (60 streams total) with libx264 consumes about 48 cores of an Intel x86-64 2.7 GHz CPU in steady state. Calculating the SSIM of each encoded chunk consumes an additional 18 cores.

# 3.2 Serving chunks to the browser

To make it feasible to deploy and test arbitrary ABR schemes, Puffer uses a "dumb" player (using the HTML5 <video> tag and the JavaScript MediaSource extensions) on the client side, and places the ABR scheme at the server. We have a 48-core server with 10 Gbps Ethernet in a well-connected datacenter. The browser opens a WebSocket (TLS/TCP) connection to a daemon on the server. Each daemon is configured with a different TCP congestion control (for the primary analysis, we used BBR [7]) and ABR scheme. Some schemes are more

Algorithm	Control	Predictor	Optimization goal	How trained
BBA	classical (prop. control)	n/a	+SSIM <i>s.t.</i> bitrate < limit	n/a
MPC-HM	classical (MPC)	classical (HM)	$+\overline{\text{SSIM}}$ , –stalls, – $\Delta$ SSIM	n/a
RobustMPC-HM	classical (robust MPC)	classical (HM)	$+\overline{\text{SSIM}}$ , –stalls, – $\Delta$ SSIM	n/a
Pensieve	learned (DNN)	n/a	+bitrate, -stalls, - $\Delta$ bitrate	reinforcement learning in simulation
Emulation-trained Fugu	classical (MPC)	learned (DNN)	$+\overline{\text{SSIM}}$ , –stalls, – $\Delta$ SSIM	supervised learning in emulation
Fugu	classical (MPC)	learned (DNN)	$+\overline{\text{SSIM}}$ , $-\text{stalls}$ , $-\Delta \text{SSIM}$	supervised learning in situ

**Figure 5:** Distinguishing features of algorithms used in the experiments. HM = harmonic mean of last five throughput samples. MPC = model-predictive control. DNN = deep neural network.

efficiently implemented than others; on average the CPU load from serving client traffic (including TLS, TCP, and ABR) is about 5% of an Intel x86-64 2.7 GHz core per stream. Sessions are randomly assigned to serving daemons. Users can switch channels without breaking their TCP connection and may have many "streams" within each session.

Puffer is not a client-side DASH [26] (Dynamic Adaptive Streaming over HTTP) system. Like DASH, though, Puffer is an ABR system streaming chunked video over a TCP connection, and runs the same ABR algorithms that DASH systems can run. We don't expect this architecture to replace client-side ABR (which can be served by CDN edge nodes), but we expect its conclusions to translate to ABR schemes broadly. The Puffer website works in the Chrome, Firefox, and Edge browsers, including on Android phones, but does not play in the Safari browser or on iOS (which lack support for the MediaSource extensions or Opus audio).

# 3.3 Hosting arbitrary ABR schemes

We implemented buffer-based control (BBA), MPC, RobustMPC, and Fugu in back-end daemons that serve video chunks over the WebSocket. We use SSIM in the objective functions for each of these schemes. For BBA, we used the formula in the original paper [17] to choose reservoir values consistent with a 15-second maximum buffer.

**Deploying Pensieve for live streaming.** We use the released Pensieve code (written in Python with TensorFlow) directly. When a client is assigned to Pensieve, Puffer spawns a Python subprocess running Pensieve's multi-video model.

We contacted the Pensieve authors to request advice on deploying the algorithm in a live, multi-video, real-world setting. The authors recommended that we use a longer-running training and that we tune the entropy parameter when training the multi-video neural network. We wrote an automated tool to train 6 different models with various entropy reduction schemes. We tested these manually over a few real networks, then selected the model with the best performance. We modified the Pensieve code to set video\_num\_chunks to 43200, indicating 24 hours of video, so that Pensieve does not expect the video to end before a user's session completes. We were not able to modify Pensieve to optimize SSIM or to consider

the individual filesizes of each chunk; it considers the average bitrate of each Puffer stream. We adjusted the video chunk length to 2.002 seconds and the buffer threshold to 15 seconds to reflect our parameters. For training data, we used the authors' provided script to generate 1000 simulated videos as training videos, and a combination of the FCC and Norway traces linked to in the Pensieve codebase as training traces.

# 3.4 The Puffer experiment

To recruit participants, we purchased Google and Reddit ads for keywords such as "live tv" and "tv streaming," and paid people on Amazon Mechanical Turk to stream video from Puffer. We were featured in press articles as a way to watch popular live events (including the Super Bowl, the World Cup, and other sporting events, "Bachelor in Paradise," etc.). Our current average load is about 50 stream-days per day. Popular events bring large spikes ( $> 20 \times$ ) over baseline load.

Starting from the beginning of 2019, we have streamed 14.2 years of video to 55,897 registered study participants using 61,682 unique IP addresses. About seven months of that period was spent on a randomized trial comparing Fugu with other algorithms (MPC, RobustMPC, Pensieve, and BBA); we refer to this as the primary experiment. This period saw 337,170 streaming sessions, and a total of 1,595,356 individual streams. A full experimental-flow diagram in the standardized CONSORT format [32] is in the appendix (Figure A1).

Metrics and statistical uncertainty. We record throughput traces and client telemetry (a full description is in the appendix) and calculate a set of figures to summarize each stream: the total time between the first and last recorded events of the stream, the startup time, the total watch time between the first and last successfully played portion of the stream, the total time the video is stalled for rebuffering, the average SSIM, and the chunk-by-chunk variation in SSIM. The ratio between "total time stalled" and "total watch time" is known as the rebuffering ratio or stall ratio, and is widely used to summarize the performance of streaming video systems [20].

We observe considerable heavy-tailed behavior in most of these statistics. Watch times are skewed (Fig. 10), and rebuffering, while important to QoE, is a rare phenomenon. Of the 458,801 eligible streams considered for the primary analysis across all five ABR schemes, only 15,788 (3%) of those streams had *any* stalls, mirroring commercial services [20].

These skewed distributions create more room for the play of chance to corrupt the bottom-line statistics summarizing a scheme's performance—even two identical schemes will see considerable variation in average performance until a substantial amount of data is assembled. In this study, we worked to quantify the statistical uncertainty that can be attributed to the play of chance in assigning sessions to ABR algorithms. We calculate confidence intervals on rebuffering ratio with the bootstrap method [12], simulating streams drawn empirically from each scheme's observed distribution of rebuffering ratio as a function of stream duration. We calculate confidence intervals on average SSIM using the formula for weighted standard error, weighting each stream by its duration.

These practices result in substantial confidence intervals: with 1.75 years of data for each scheme, the width of the 95% confidence interval on a scheme's stall ratio is between  $\pm 10\%$  and  $\pm 17\%$  of the mean value. This is comparable to the magnitude of the total benefit reported by some academic work that used much shorter real-world experiments. Even a recent study of a Pensieve-like scheme on Facebook, which collected data on 30 million streams, did not detect a change in rebuffering ratio outside the level of statistical noise.

We conclude that considerations of uncertainty in real-world learning and experimentation, especially given uncontrolled data from the Internet with real users, deserve further study. Strategies to import real-world data into repeatable emulators [42] or reduce their variance [24] will likely be helpful in producing robust learned networking algorithms.

#### 4 Fugu: design and implementation

Fugu is a control algorithm for bitrate selection, designed to be feasibly trained in place (in situ) on a real deployment environment. It consists of a classical controller (model predictive control, the same as in MPC-HM), informed by a nonlinear predictor that can be trained with supervised learning.

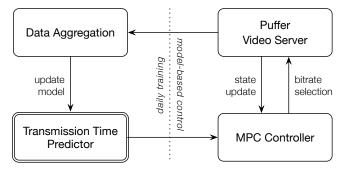


Figure 6: Overview of Fugu

Figure 6 shows Fugu's high-level design. Fugu runs on the

server, making it easy to update its model and aggregate performance data across clients over time. Clients send necessary telemetry, such as buffer levels, to the server.

The controller, described in Section 4.4, makes decisions by following a classical control algorithm to optimize an objective QoE function (§4.1) based on predictions for how long each chunk would take to transmit. These predictions are provided by the Transmission Time Predictor (TTP) (§4.2), a neural network that estimates a probability distribution for the transmission time of a proposed chunk with given filesize.

# 4.1 Objective function

For each video chunk  $K_i$ , Fugu has a selection of versions of this chunk to choose from,  $K_i^s$ , each with a different size s. As with prior approaches, Fugu quantifies the QoE of each chunk as a linear combination of video quality, video quality variation, and stall time [43]. Unlike some prior approaches, which use the average compressed bitrate of each encoding setting as a proxy for image quality, Fugu optimizes a perceptual measure of picture quality—in our case, SSIM. This has been shown to correlate with human opinions of QoE [10]. We emphasize that we use the exact same objective function in our version of MPC and RobustMPC as well.

Let Q(K) be the quality of a chunk K, T(K) be the uncertain transmission time of K, and  $B_i$  be the current playback buffer size. Fugu defines the QoE of  $K_i^s$  (following [43]) as

$$QoE(K_i^s, K_{i-1}) = Q(K_i^s) - \lambda |Q(K_i^s) - Q(K_{i-1})| - \mu \cdot \max\{T(K_i^s) - B_i, 0\},$$
(1)

where  $\lambda$  and  $\mu$  are configuration constants for how much to weight video quality variation and rebuffering. The last term  $\max\{T(K_i^s) - B_i, 0\}$  describes the stall time experienced by sending  $K_i^s$ . Fugu plans a trajectory of sizes s of the future H chunks to maximize their expected total QoE.

## 4.2 Transmission Time Predictor (TTP)

Once Fugu decides which chunk to send, two portions of the QoE become known: the video quality and video quality variation. The remaining uncertainty is the stall time. The server knows the current playback buffer size, so what it needs to know is the transmission time: how long will it take for the client to receive the chunk? Given an oracle that reports the transmission time of any chunk, the MPC controller can compute the optimal plan to maximize QoE.

Fugu uses a trained neural-network transmission-time predictor to approximate the oracle. For each chunk in the fixed horizon, we train a separate predictor. E.g., if optimizing for the total QoE of the next five chunks, five neural networks are trained. (Multiple networks in parallel are functionally equivalent to one that takes the future time step as a variable. We have observed equivalent performance with both approaches, but training multiple DNNs lets us parallelize training.)

Each TTP network takes as input a vector of:

- 1. sizes of past t chunks:  $K_{i-t}, \ldots, K_{i-1}$ ,
- 2. transmission times of past t chunks  $T_{i-1}, \ldots, T_{i-1}$ ,
- 3. internal TCP statistics (Linux top\_info structure),
- 4. size of the chunk to be transmitted.

The TCP statistics include the current congestion window size, the number of unacknowledged packets in flight, the smoothed RTT estimate, the minimum RTT, and the estimated throughput (tcpi\_delivery\_rate).

Prior approaches have used Harmonic Mean (HM) [43] or a Hidden Markov Model (HMM) [38] to predict a single throughput for the entire lookahead horizon. In contrast, the transmission-time predictor outputs a probability distribution  $\hat{T}(K_i^s)$  over the transmission time of  $K_i^s$ .

## 4.3 Training the TTP

Puffer collects training data  $\mathcal{D}$  by saving client telemetry from real usage, aggregating pairs of (a) the input 4-vector and, (b) the true transmission time for the chunk. We train the TTP on  $\mathcal{D}$  with standard supervised learning: the training minimizes the cross-entropy loss between the output probability distribution and the discretized actual transmission time using stochastic gradient descent.

We retrain the TTP every day, using training data collected on Puffer over the prior 14 days, to avoid the effects of dataset shift and catastrophic forgetting [30,31]. Within the 14-day window, we weight more recent days more heavily, and we shuffle the sampled data to remove correlation in the sequence of inputs. The weights from the previous day's model are loaded to warm-start the retraining.

## 4.4 Model-based controller

Our MPC controller (used for MPC-HM, RobustMPC-HM, and Fugu) is a stochastic optimal controller that maximizes the expected cumulative QoE in Equation 1. It queries TTP for predictions of transmission time and outputs a plan  $K_i^s, K_{i+1}^s, \ldots, K_{i+H-1}^s$  by value iteration [6]. After sending  $K_i^s$ , the controller observes and updates the input vector passed into TTP, and replans again for the next chunk.

Given the current playback buffer level, let  $v_i^*(B_i, K_{i-1})$  denote the maximum expected sum of QoE that can be achieved in the H-step lookahead horizon given the last sent chunk  $K_{i-1}$ . We have value iteration as follows:

$$\begin{aligned} v_i^*(B_i, K_{i-1}) &= \max_{K_i^s} \Big\{ \sum_{T_i} \Pr[\hat{T}(K_i^s) = T_i] \cdot \\ & (QoE(K_i^s, K_{i-1}) + v_{i+1}^*(B_{i+1}, K_i^s)) \Big\}, \end{aligned}$$

where  $Pr[\hat{T}(K_i^s) = T_i]$  is the probability for TTP to output a discretized transmission time  $T_i$ , and  $B_{i+1}$  can be derived by

system dynamics once  $T_i$  is estimated. The controller computes the optimal trajectory by solving the above value iteration with dynamic programming (DP). To make the DP computational feasible, it discretizes  $B_i$  into bins and uses forward recursion with memoization to only compute for relevant  $v_i^*(B_i, K_{i-1})$ .

# 4.5 Implementation

TTP takes as input the past t = 8 chunks, and outputs a probability distribution over 21 bins of transmission time:  $[0,0.25), [0.25,0.75), [0.75,1.25), \dots, [9.75,\infty), \text{ with } 0.5 \text{ sec-}$ onds as the bin size except for the first and the last bins. TTP is a fully-connected neural network, with two hidden layers with 64 neurons each. We tested different TTPs with various numbers of hidden layers and neurons, and found similar training losses across a range of conditions for each. We implemented TTP and the training in PyTorch, but we load the trained model in C++ when running on the production server for performance. A forward pass of TTP's neural network in C++ imposes minimal overhead per chunk (less than 0.3 ms on average on a recent x86-64 core). The MPC controller optimizes over H = 5 future steps (about 10 seconds) by solving value iteration. We set  $\lambda = 1$  and  $\mu = 100$  to balance the conflicting goals in QoE. Each retraining takes about 6 hours on a 48-core server.

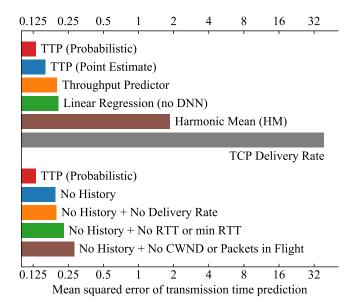
#### 4.6 Ablation study of TTP features

We performed an ablation study to assess the impact of the TTP's features (Fig. 7). Here are the more notable results:

Use of low-level congestion-control statistics. The TTP's nature as a DNN lets it consider a variety of noisy inputs, including low-level congestion-control statistics. We feed the kernel's tcp\_info structure to the TTP, and find that several of these fields contribute positively to the TTP's accuracy, especially the RTT, CWND, and number of packets in flight (Figure 7). Although client-side ABR systems cannot typically access this structure directory because the statistics live on the sender, these results should motivate the communication of richer data to ABR algorithms wherever they live.

**Transmission-time prediction.** The TTP explicitly considers the chunk size of  $K_i$  and outputs a predicted duration, a more powerful approach than a generating a single throughput estimate. It is well known in ABR streaming and congestion control that transmission time does not scale linearly with filesize [5]. We compared the accuracy of the TTP against an equivalent throughput predictor (keeping everything else unchanged) and found the TTP's predictions were much more accurate (Figure 7).

**Prediction with uncertainty.** The TTP outputs a *probability* 



**Figure 7:** Ablation study of Fugu's Transmission Time Predictor (TTP). Removing each of the TTP's inputs, outputs, or features reduced its ability to predict the transmission time of a video chunk. A non-probabilistic TTP ("Point Estimate") and one that predicts throughput without regard to chunk size ("Throughput Predictor") both performed markedly worse. TCP-layer statistics (RTT, CWND) were also helpful.

distribution of transmission times. This additional information allows for better decision making, compared with a single point estimate without uncertainty. We evaluated the expected accuracy of a probabilistic TTP vs. an equivalent "maximum likelihood" version, and found a considerable improvement in prediction accuracy with the former (Figure 7).

In addition, to confirm the relationship between prediction accuracy and performance of the entire ABR system, we deployed a point-estimate version of Fugu on Puffer in August 2019 and collected 39 stream-days of data with this scheme. It performed much worse than normal Fugu: the rebuffering ratio was  $3-9\times$  worse, without significant improvement in SSIM (data not shown).

Use of neural network. Although it is often said that "data > algorithms" in machine learning [16], we did find a significant benefit to the use of a deep neural network in this application. A linear-regression model (equivalent to a single-layer neural network), trained the same, performs much worse on prediction accuracy (Figure 7).

We also deployed this scheme on the Puffer website and collected 107 stream-days of data in September 2019 to measure its end-to-end ABR performance. Again, the lower prediction accuracy was harmful to the bottom line; its rebuffering ratio was  $2-5 \times$  worse (data not shown).

**Daily retraining.** To validate our practice of daily retraining,

we conducted a randomized controlled trial of several "out-of-date" versions of the TTP on the Puffer website between Aug. 7 and Aug. 30, 2019. We compared versions of the TTP trained in February, March, April, and May, compared with the "live" TTP that is retrained each day. We collected between 106 and 131 stream-days of data for each of these schemes. Somewhat to our surprise, we were not able to detect a significant difference in performance between any of these ABR schemes—even comparing the "February" TTP against one that was retrained each day in August. We certainly see a benefit from learning *in situ* (Figure 11 shows catastrophic behavior from a TTP learned in a network emulation), but our practice of daily retraining in situ appears to be overkill.

## 5 Experimental Results

We now present findings from our experiments with the Puffer study, including the evaluation of Fugu. Our main results are shown in Figure 8. In summary, we conducted a parallel-group, blinded-assignment, randomized controlled trial of five ABR schemes between Jan. 19 and Aug. 7, and between Aug. 30 and Sept. 12, 2019 (the cutoff for this submission). The data include 8.5 stream-years of data split across five algorithms, counting all streams that played at least 4 seconds of video. A standardized diagram of the experimental flow is available in the appendix (Figure A1).

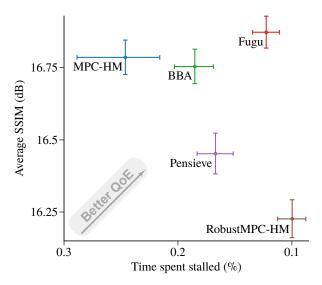
We found that old-fashioned "buffer-based" control performs surprisingly well, despite its status as a frequently outperformed research baseline. In the overall dataset (Figure 8, left-hand side), BBA outperforms MPC-HM on stalls and is statistically indistinguishable on video quality. It outperforms Pensieve on quality and is indistinguishable on stalls. RobustMPC-HM has an even lower stall rate, at the cost of considerable loss of quality. Among "slow" network paths (those with average throughput less than 6 Mbit/s; see Figure 8, right-hand side), Pensieve shows an advantage in reducing the stall rate, again at a considerable cost in quality.

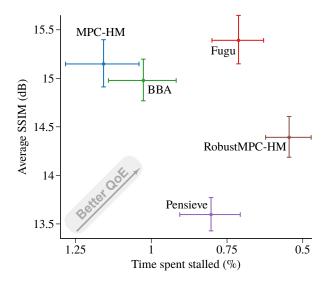
The only scheme to consistently outperform BBA in both stalls and quality was Fugu, but only when *all* features of the TTP were used. If we remove the probabilistic "fuzzy" nature of Fugu's predictions, *or* the "depth" of the neural network, *or* the prediction of transmission time as a function of chunk size (and not simply throughput), Fugu forfeits its advantage (§§4.6). Fugu also outperformed other schemes in terms of SSIM variability (Figure 1). The TTP's use of low-level TCP statistics was helpful on a cold start to a new session; this allowed Fugu to begin at a higher quality (Figure 9).

We conclude that robustly beating "simple" algorithms with machine learning may be surprisingly difficult, notwith-standing promising results in contained environments such as simulators and emulators. The gains that learned algorithms have in optimization or smarter decision making may come at a tradeoff in brittleness or sensitivity to heavy-tailed behavior.

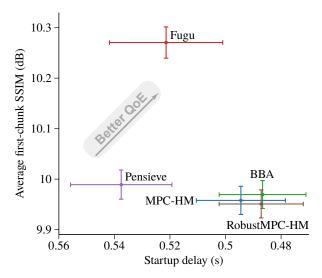
Primary experiment (N=458,801, duration 8.5y)

Slow network paths (N=100,500, duration 1.3y)





**Figure 8: Main results.** In a blinded randomized controlled trial that included 8.5 years of video streamed to 44,907 client IP addresses over a seven-month period, Fugu reduced the fraction of time spent stalled (except with respect to RobustMPC-HM), increased SSIM, and reduced SSIM variation within each stream (tabular data in Figure 1). "Slow" network paths have mean TCP *delivery\_rate* less than 6 Mbit/s; following prior work [23,43], these paths are more likely to require nontrivial bitrate-adaptation logic. Such streams accounted for 16% of overall viewing time and 82% of stalls. Error bars show 95% confidence intervals.



**Figure 9:** On a cold start, Fugu's ability to bootstrap ABR decisions from congestion-control statistics (e.g., RTT) boosts initial quality.

## 5.1 Fugu users streamed for longer

We observed significant differences in the session durations of users across algorithms (Figure 10). Users whose sessions were assigned to Fugu chose to remain on the Puffer video player about 10–20% longer, on average, than those assigned to other schemes. Users were blinded to the assignment, and

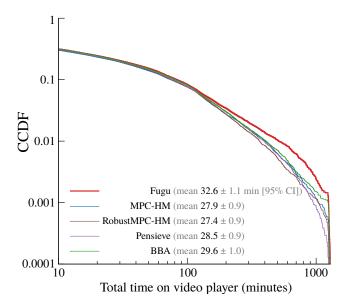
we believe the experiment was carefully executed not to "leak" details of the underlying scheme (MPC and Fugu even share most of their codebase). The average difference was driven solely by the upper 5% tail of viewership duration (sessions lasting more than 2.5 hours)—viewers assigned to Fugu are much more likely to keep streaming beyond this point, even as the distributions are nearly identical until then.

Time-on-site is a figure of merit in the video-streaming industry and might be increased by delivering better-quality video, but we simply do not know enough about what is driving this phenomenon.

#### 5.2 The benefits of learning in situ

Each of the ABR algorithms we evaluate was evaluated in emulation in prior works [23,43]. Notably, the results in those works are qualitatively different from some of the real world results we have seen here—for example, buffer-based control outperforming MPC-HM and Pensieve.

To investigate this further, we constructed an emulation environment similar to that used in [23]. This involved running the Puffer media server locally, and launching headless Chrome clients inside mahimahi [27] shells to connect to the server. Each mahimahi shell imposed a 40 ms end-to-end delay on traffic originating inside it and limited the downlink capacity over time to match the capacity recorded in a set of FCC broadband network traces [8]. As in the Pensieve evaluation, uplink speeds in all shells were capped at 12 Mbps. Within this test setup, we automated 12 clients to repeatedly



**Figure 10:** Users randomly assigned to Fugu chose to remain on the Puffer video player about 10%–20% longer, on average, than those assigned to other schemes. Users were blinded to the assignment. This average difference was driven solely by the upper 5% tail (sessions lasting more than 2.5 hours). Timeon-site is a figure of merit in the industry and may correlate with QoE, but we do not fully understand this effect.

connect to the media server, which would play a 10 minute clip recorded on NBC over each network trace in the dataset. Each client was assigned to a different combination of ABR and CC algorithms, and played the 10 minute video repeatedly over more than 15 hours of FCC traces. The results from this experiment are depicted in Figure 11.

We trained a version of Fugu in this emulation environment to compare its performance with a version trained in situ (on data from Puffer). Compared with the in situ Fugu—or with every other ABR scheme—the real-world performance of emulation-trained Fugu was horrible (Figure 11, middle panel). Looking at the other ABR schemes, it is illuminating to comparing Figure 11 with Figure 8—the emulation results differ markedly from the real world. In emulation (left side of figure), almost every algorithm tested lies somewhere along the SSIM/stall frontier, with Pensieve rebuffering the least and MPC delivering the highest quality video, and the other algorithms lying somewhere in between. In the real experiment (middle of figure), we see a more muddled picture, with Fugu apparently outperforming other algorithms in both quality and stall time. These results suggest research opportunities in constructing network emulators that capture additional dynamics of the real Internet.

#### 5.3 Remarks on Pensieve and RL for ABR

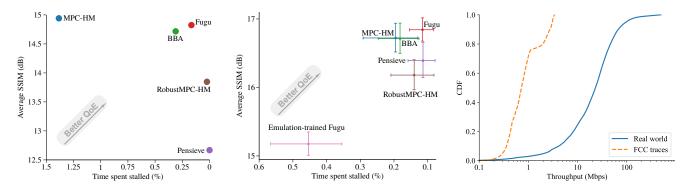
The original Pensieve paper [23] demonstrated that Pensieve outperformed MPC-HM, RobustMPC-HM, and BBA in both simulation-based tests and in video streaming tests on a low and high speed real-world networks. Our results differ; we believe the mismatch may have occurred for several reasons.

First, we have found that emulation-based training and testing (or, at least, mahimahi tests with the FCC dataset) do not capture the vagaries of the real-world paths seen in the Puffer study. Unlike real-world randomized trials, trace-based emulators and simulators allow experimenters to run two different algorithms on the *same* conditions, eliminating the effect of the play of chance in giving different algorithms a different distribution of watch times, network behaviors, etc. However, it is difficult to characterize the *systematic* uncertainty that comes from selecting a set of traces that may omit the variability or heavy-tailed nature of a real deployment experience (both network behaviors as well as user behaviors, such as watch duration).

Reinforcement learning (RL) schemes such as Pensieve may be at a particular disadvantage from this phenomenon. Unlike supervised learning schemes that can learn from training "data," reinforcement learning requires a training environment to respond to a sequence of control decisions and decide on the appropriate consequences and reward. That environment could be real life instead of a simulator, but the level of statistical noise we observe would make this type of learning extremely slow or require an extremely broad deployment of algorithms in training. Reinforcement learning relies on being able to slightly vary a control action and detect a change in the resulting reward. By our calculations, the variability of inputs is such that it takes about 2 stream-years of data to reliably distinguish two ABR schemes whose innate "true' performance differs by 15%. To make RL practical, future work may need to explore techniques to reduce this variability [24] or construct more faithful simulators and emulators that model tail behaviors [42].

Second, most of the evaluation of Pensieve in the original paper focused on training and evaluating Pensieve using a single test video. As a result, the state space that model had to explore was inherently more limited. Evaluation of the Pensieve "multi-video model"—which we have to use for our experimental setting—was more limited. Our results are more consistent with a recent large-scale study of a Pensieve-multi-video-like scheme on 30 million streams at Facebook [22]; this study found a small benefit in bitrate over Facebook's default ABR scheme, and no significant benefit in rebuffering.

Finally, Pensieve optimizes a QoE metric centered around bitrate as a proxy for video quality. Altering this would have required significant surgery to provide new values to the Pensieve neural network over time. Figure 4 shows that Pensieve was the #2 scheme in terms of bitrate (below BBA) in the primary analysis. We emphasize that our findings do not indicate



**Figure 11: Left:** performance in emulation, run in mahimahi [27] using the FCC traces [8], following the method of Pensieve [23]. **Middle:** experimental results from Puffer. During Jan.—April 2019, we randomized sessions to a set of algorithms including "emulation-trained Fugu," and show results of 45,695 streams, 328 stream-days of data from this time period. Training on these traces did not generalize to the real-world setting. **Right:** comparison of throughput distribution on FCC traces and Puffer, estimated using the experimental results from the left two figures.

that Pensieve cannot be a useful ABR algorithm, especially in a scenario where similar, pre-recorded video is played over a familiar set of known networks.

#### 6 Limitations

The design of the Puffer experiment and the Fugu system are subject to important limitations that may affect their performance and generalizability.

# **6.1** Limitations of the experiments

Our randomized controlled trial represents a rigorous, but necessarily "black box," study of ABR algorithms for video streaming. We don't know the true distribution of network paths and throughput-generating processes; we don't know the participants or why the distribution in watch times differs by assigned algorithm; and we don't know how to emulate these behaviors accurately in a controlled environment.

We have supplemented this black-box work with ablation analyses to relate the real-world performance of Fugu to the  $l^2$  accuracy of its predictor, and have studied various ablated versions of Fugu in deployment. However, ultimately part of the reason for this paper is that we *cannot* replicate the experimental findings outside the real world—a real world whose behavior is noisy and takes lots of time to measure precisely. That may be an unsatisfying conclusion, and we doubt it will be the final word on this topic. Perhaps it will become possible to model enough of the vagaries of the real Internet "in silico" to enable the development of robust control strategies without extensive real-world experiments.

It is also unknown to what degree Puffer's results—which are about a single server with 10 Gbps connectivity in a well-provisioned datacenter, sending to clients across our entire country over the wide-area Internet—generalize to a different server at a different institution, much less the more typical

paths between a user on an access network and their nearest CDN edge node. We don't know for sure if the pre-trained Fugu model would work in a different location, or whether training a new Fugu based on data from that server would yield comparable results. Our results show that learning *in situ* works, but we don't know how specific the *situs* needs to be.

Although we believe that past research papers may have underestimated the uncertainties in real-world measurements with realistic Internet paths and users, we also may be guilty of underestimating our own uncertainties or—also possible—emphasizing uncertainties that are only relevant to small or medium-sized academic studies, such as ours, and irrelevant to the industry. The current load on Puffer is about 50 concurrent streams on average, meaning we collect about 50 stream-days of data per day. Our primary analysis covers about 1.7 stream-years of data per scheme collected over a seven-month period, and was sufficient to measure its performance metrics to within about  $\pm 15\%$  (95% CI).

By contrast, we understand YouTube has an average load over 50 *million* concurrent streams at any given time. We imagine the considerations of conducting data-driven experiments at this level may be completely different—perhaps less about statistical uncertainty, and more about systematic uncertainties and the difficulties of running experiments and accumulating so much data. (We also understand that YouTube is only able to measure its own performance once every 48 hours because of the vastness of data that needs to be aggregated.)

Some of Fugu's performance (and that of MPC, RobustMPC, and BBA) relative to Pensieve may be due to the fact that these four schemes received more information as they ran—namely, the SSIM of each possible version of each future chunk—than did Pensieve. It is possible that an "SSIM-aware" Pensieve might perform better. We tried to approximate this sort of scheme (an SSIM-aware neural network trained in emulation) with the "Emulation-trained Fugu" benchmark

(Figure 11). The load of calculating SSIM for each encoded chunk is not insignificant—about an extra 40% on top of the cost of encoding the video.

## 6.2 Limitations of Fugu

There is a sense that data-driven algorithms that more "heavily" squeeze out performance gains may also put themselves at risk to brittleness when a deployment environment drifts from one where the algorithm was trained. In that sense, it is hard to say whether Fugu's performance might decay catastrophically some day. We tried and failed to demonstrate a quantitative benefit from *daily* retraining over "every six months" retraining, but at the same time, we cannot be sure that some surprising detail tomorrow—e.g., a new user from an unfamiliar network—won't send Fugu into a tailspin before it can be retrained. Our eight months of data on a growing userbase suggests, but doesn't guarantee, robustness to a changing environment.

Fugu does not consider several issues that other research has concerned itself with—e.g., being able to "replace" already-downloaded chunks in the buffer with higher quality versions [35], or optimizing the joint QoE of multiple clients who share a congestion bottleneck.

Fugu is not tied as tightly to the TCP or congestion control as it might be—for example, Fugu could wait to send a chunk until the TCP sender tells it that there is a sufficient congestion window for most of the chunk (or the whole chunk) to be sent immediately. Otherwise, it *might* choose to wait and make a better-informed decision later. Fugu does not schedule the transmission of chunks—it will always send the next chunk as long as the client has room in its playback buffer.

## 7 Conclusion

Machine-learned systems in computer networking sometimes describe themselves as achieving near-"optimal" performance, based on results in a contained or modeled version of the problem [23, 34, 36].

In this paper, we suggest that these efforts can benefit from considering a broader notion of performance and optimality. Good, or even near-optimal, performance in a simulator or emulator does not necessarily predict good performance over the wild Internet, with its variability and heavy-tailed distributions. It remains a challenging problem to gather the appropriate training data (or in the case of RL systems, training environment) to properly learn and validate such systems.

In this paper, we asked: what does it take to create a learned ABR algorithm that robustly performs well over the wild Internet? In effect, our best answer is to cheat: train the algorithm in situ on data from the real deployment environment, and use an algorithm whose structure is sophisticated enough (a neural network) and yet also simple enough (a predictor

amenable to supervised learning on data, feeding a classical controller) to benefit from that kind of training.

Over the last eight months, we have streamed 14.2 years of video to 56,000 users across the Internet. Sessions are randomized in blinded fashion among algorithms, and client telemetry is recorded for analysis. The Fugu algorithm robustly outperformed other schemes, both simple and sophisticated, on objective measures (SSIM, stall time, SSIM variability) and increased the duration that users chose to continue streaming.<sup>3</sup>

We have found the Puffer approach an enormously powerful tool for networking research—it is very fulfilling to be able to "measure, then build" [3] to iterate rapidly on new ideas and gain feedback. Accordingly, we are opening Puffer as an "open research" platform. Along with this paper, we are publishing our full archive of traces and results on the Puffer website. The system posts new data each day, along with a summary of results from the ongoing experiments, with confidence intervals similar to those in this paper. (The format is described in the appendix.) We will redact some fields from the public archive (e.g., IP address and user ID) but are willing to work with researchers in the community on access to this data as appropriate. Puffer and Fugu are also open-source software.<sup>4</sup>

We plan to operate Puffer for several years and invite researchers to train and validate new algorithms for ABR control, network and throughput prediction, and congestion control on its traffic. We believe that Puffer could serve as a helpful "medium-scale" stepping-stone for new algorithms, partway between the flexibility of network emulation and the vastness of data—but also conservatism about deploying new algorithms—of commercial services. We are eager to collaborate with and learn from the community's ideas on how to design and deploy robust learned systems for the Internet.

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<sup>&</sup>lt;sup>3</sup>We do not claim this as an accomplishment per se.

<sup>&</sup>lt;sup>4</sup>https://github.com/StanfordSNR/puffer

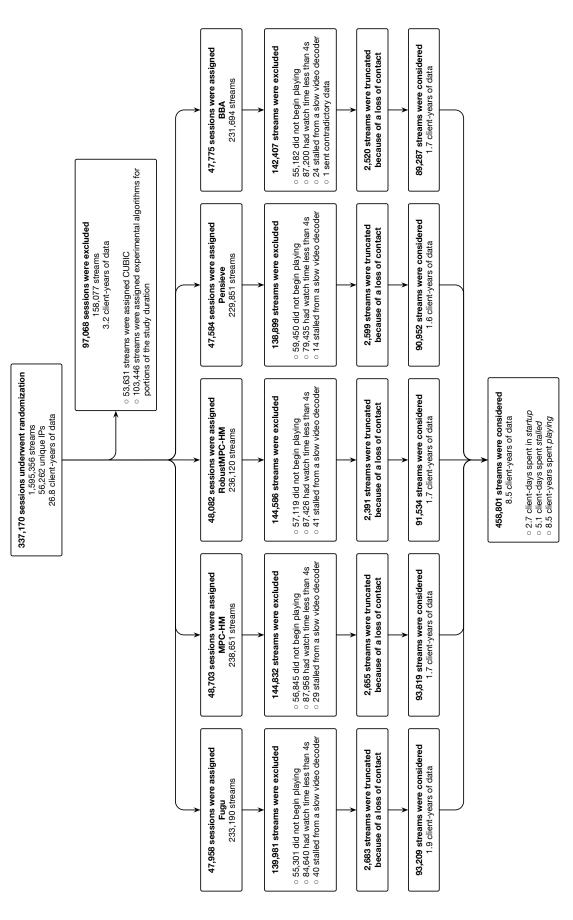
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# A Randomized trial flow diagram



Aug. 30-Sept. 12, 2019. A "session" represents one visit to the Puffer video player and may contain many "streams." Reloading starts a new session, but changing channels only starts a new stream and does not change TCP connections or ABR algorithms. A large number of streams never began playing; these were often users Figure A1: CONSORT-style diagram [32] of experimental flow for the primary results (Figures 1 and 8), obtained during the period Jan. 1-Aug. 7, 2019, and rapidly changing channels or using an incompatible browser.

Under anonymous submission (Sept. 19, 2019)

# **B** Description of open data

The open data we release comprise different sets of data — "measurements" — with each measurement containing a piece of information from a video server or a client. Below we highlight the format of interesting fields in three measurements essential for analysis of this data: video\_sent, video\_acked, and client\_buffer.

video\_sent collects a data point every time an Puffer server sends a video chunk to a client. Each data point contains:

- time: epoch time when the chunk is sent.
- stream\_id: a unique ID to identify a video stream.
- expt\_id: a unique ID for each experimental group.
  expt\_id can be used to retrieve the configuration (e.g., ABR, congestion control) tested in the corresponding experimental group.
- size: size of the chunk.
- ssim index: SSIM of the chunk.
- cwnd: current congestion window size (tcpi\_snd\_cwnd) in tcp\_info.
- in\_flight: number of unacknowledged packets in flight (tcpi\_unacked tcpi\_sacked tcpi\_lost + tcpi\_retrans).

- min\_rtt: minimum RTT (tcpi\_min\_rtt).
- rtt: smoothed RTT estimate (tcpi\_rtt).
- delivery\_rate: estimate of TCP throughput (tcpi\_delivery\_rate).

video\_acked collects a data point every time an Puffer server receives a video chunk acknowledgement from a client. Each data point can be matched to a data point in video\_sent (if the chunk is ever acknowledged) and used to calculate the transmission time of the chunk.

client\_buffer collects client-side buffer information on a regular interval and when certain events occur. Each data point contains:

- event: event type, e.g., was this triggered by a regular report every quarter second, or because the client stalled or began playing.
- buffer: playback buffer size.
- cum\_rebuf: cumulative rebuffer time in the current stream.

Between January 1 and September 12, 2019, we collected 261,280,238 data points in video\_sent, 264,374,831 data points in video\_acked, and 1,729,618,482 data points in client buffer.