MEASUREMENTS ON LARGE-SCALE PEER-ASSISTED
LIVE STREAMING: A SURVIVAL ANALYSIS APPROACH

by

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Graduate Department of Electrical and Computer Engineering
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Abstract

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In large-scale peer-assisted live streaming systems with hundreds of online channels, it becomes critically important to investigate the lifetime pattern of streaming sessions to have a better understanding of peer dynamics. Aiming to improve performance of the P2P streaming systems, the goal of this thesis is twofold: 1) for popular channels, we wish to identify superior peers, that contribute a higher percentage of upload capacities and stay for a longer period of time; 2) for unpopular channels, we seek to explore factors that affect the peer instability. Utilizing more than 130 GB worth of run-time traces from a large-scale real-world live streaming system, UUSee, we conduct a comprehensive and in-depth statistical analysis. Using survival analysis techniques, we discover critical factors that may influence the longevity. Based on the Cox regression models we built, we also discuss several interesting insights from our measurement results.
To my parents
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Chapter 1

Introduction

1.1 Challenges of P2P Live Streaming

Inspired by ideas in peer-to-peer file sharing systems [1, 2], networking researchers have designed and implemented several live peer-assisted streaming applications in recent years [19,31]. In industry, production live P2P multimedia streaming solutions, such as PPLive [3], UUSee [8], PPStream [4], TVAnts [7] and SOPCast [5], have been successfully deployed in the real world at a large scale, with hundreds of channels and hundreds of thousands of users at any given time [16,29]. A salient advantage of P2P live streaming systems is the use of peer upload bandwidth contribution to complement bandwidth supplies from a limited number of dedicated streaming servers, mitigating their load and allowing better scalability.

An important test to evaluate the scalability and effectiveness of live P2P streaming protocols is how well a streaming system can scale up to a number of peers beyond the threshold of what servers can sustain. Even though it is theoretically possible to scale to an unlimited number of peers, as real-world peers suffer from upload bandwidth limitations such as NAT traversal challenges and firewalls, real-world systems with a limited pool of server bandwidth supplies can only sustain a limited number of peers,
spreading across hundreds of channels. When such a sustainable threshold is reached and then breached, some of the peers are bound to suffer from reduced streaming quality, characterized by the continuity of playback.

In such critical conditions, such as flash crowds, it is important to preserve and sustain the streaming quality of two types of “superior” peers: those who contribute a higher ratio of their upload bandwidth, and those who are stable for a long period of time. The best peers would, of course, have both excellent longevity and high upload contribution ratio. While favoring such superior peers may sacrifice a small portion of non-superior peers in terms of streaming quality, it must be realized that if these superior peers are not given preference, the risk of their departure would further disturb the stability and bandwidth supply-demand balance in the system, which may escalate to even higher levels of volatility. Such deterioration of stability and deficit of bandwidth may spiral out of control.

We have also discovered that in several commercial live P2P streaming systems, peer populations across different channels are widely uneven distributed: there may be thousands of concurrent users watching a popular channel, and no more than a few hundred of peers in an unpopular channel. These unpopular channels, usually representing the majority of the available channels in the streaming system, generally experience lower streaming quality, compared to aforementioned popular channels. A short peer lifespan — severe peer volatility — in such unpopular channels reveals a less than desirable situation that may lead to a downward spiral of peer population: On one hand, the low streaming quality in an unpopular channel may lead to short peer stay in the channel; on the other hand, the more severe peer churn further exacerbates the streaming quality of existing peers.

Aiming to improve the performance in both popular and unpopular streaming channels, we conduct a comprehensive and in-depth statistical analysis based on more than 130 GB worth of run-time traces in a large-scale real-world P2P live streaming
system, UUSee. The system that UUSee Inc. operates is among the top three commercial systems in mainland China, along with PPLive and PPStream. Our objective is very clear: we wish to identify critical performance metrics as risk factors that may influence the longevity of peers in both popular and unpopular channels. To achieve this, we have parsed and imported all run-time traces into a database, where we apply survival analysis techniques such as the Cox proportional hazards model [13] and the Mantel-Haenszel log-rank test [22,23] to discover such influential factors.

1.2 Major Contributions

In recent years, significant research efforts have been devoted to the measurement and improvement of real-world peer-assisted live streaming systems. To investigate the scalability and stability of these systems, existing studies mostly focus on the measurement and characterization of P2P topologies [29], throughput levels [28], and peer churns [16]. Little attention devoted to the in-depth analysis of longevity and bandwidth contribution ratio of individual peer, which nevertheless contribute significantly to the performance of P2P live streaming system. This thesis distinguishes itself from the existing measurement work in two aspects.

Utilizing over 130 GB worth of real-world traces from a real-world P2P streaming system, UUSee, we explore influential factors to peer longevity and bandwidth contribution level in real-world popular live streaming channels. We have not only identified the key influential factors that decide the duration of peer sessions in popular channels, but also have modeled their relationship into a Cox regression model. Similarly, with respect to the bandwidth contribution ratio at each peer, we have discovered the impact of the peer initial buffering level and ISP membership, and have modeled their correlations in a linear model. As an important application of our discoveries, we have designed a superiority index for distilling superior peers from the general peer
population, and have applied the index in a natural selection algorithm to promote the session duration of high contribution peers. Our evaluations, which are based on a replay of real-world streaming traces, validate the effectiveness of this superiority index in improving the overall stability and scalability of the P2P streaming system.

Focusing on improving the streaming quality in the large number of unpopular channels in real-world P2P live streaming systems, we thoroughly characterize important factors that influence peer longevity. Our key contributions include: first, we successfully identify key factors that decide the peer longevity in unpopular channels, including the initial buffering level, incoming degree, peer joining time, and last-mile link type; second, we model their relationship into a Cox regression model, using a survival analysis approach; third, we discuss several implications of our model and derive a number of useful insights to promote peer stability in unpopular channels.

1.3 Thesis Overview

The remainder of this thesis is organized as follows.

In Ch. 2, we introduce a real-world commercial P2P live streaming system, UUSee, and present methodologies with respect to collecting UUSee run-time traces. We also briefly discuss survival analysis techniques, which will be used in the later chapters of this thesis. In the last part of this chapter, we survey existing measurement studies on P2P live streaming systems.

In Ch. 3, we first identify influential performance factors on the peer longevity in popular streaming channels, and then shift our focus to the upload contribution ratio of peers. Based on derived regression models, we construct a superiority index based on both longevity and upload contribution ratio of peers, and simulate a simple ranking mechanism in a natural selection algorithm to show the effectiveness of using the superiority index.
In Ch. 4, we explore possible factors that may affect the peer lifespan in unpopular channels, and identify critical ones as the influential factors. Then, we model the impact of influential factors using the Cox regression model, and discuss implications of our model.

In Ch. 5, we conclude this thesis and discuss the future work.
Chapter 2

Background

2.1 UUSee: A Large-Scale Peer-Assisted Live Streaming System

Supported by venture capital funding from established firms, UUSee Inc. [8] is one of the leading P2P multimedia solution providers in mainland China, featuring both legal contractual rights to most of the channels of CCTV, the official Chinese television broadcaster, and online broadcasting rights to 2008 Summer Olympics. With a large collection of streaming servers around the world, it simultaneously broadcasts over 800 live streaming channels to millions of peers, mostly encoded to high quality streams around 500 Kbps. The users of UUSee are distributed across all the major ISPs in China and over 40 countries in the world.

Similar to most state-of-the-art meshed-based P2P streaming protocols, UUSee’s streaming protocol design is based on the principle of allowing peers to serve each other by exchanging blocks of data, which are received and cached in their local playback buffers. An illustration of the UUSee streaming system is shown in Fig. 2.1. The buffer at each peer represents a sliding window of the media channel, containing blocks to be played in the immediate future. The buffer size in UUSee is 500 me-
dia blocks, and each block represents 1/3 second of media playback. Once a new peer joins a channel in UUSee, an initial set of partners (up to 50) is supplied by one of its tracking servers. The peer then establishes TCP or UDP connections with these partners, and buffer availability bitmaps (i.e., buffer maps) are exchanged periodically. During this process, it measures the throughput of the connection, and then selects a number of most suitable peers (around 30), from which it actually requests media blocks.

2.2 Collecting Real-World Traces in UUSee

2.2.1 Measurement Methodology

While the collection of most performance metrics is straightforward, in what follows, we explain our measurement methods with respect to the download and upload capacities of each peer, and the maximum sending or receiving throughput along each
P2P connection.

The download capacity of each peer is measured at the initial buffering stage of the peer, upon its first joining a streaming channel in the UUSee system. During this stage, the peer has no available blocks in its playback buffer, and can concurrently download from many supplying peers. In this case, its download bandwidth is largely saturated. Therefore, the download capacity of the peer is estimated as its maximum aggregate download rate at this initial buffering stage.

The upload capacity at each peer is measured upon its joining before the actual streaming starts, by setting up a temporary upload TCP connection with one of the nearest streaming servers. As we know, the upload bandwidth at each streaming server is mostly saturated due to its main upload functions, while the download bandwidth is largely idle. Therefore, we utilize the spare download capacity of the streaming servers, and have each peer send a randomly generated probing flow to a streaming server that is nearest to itself. The duration of the flow should be long enough for its TCP throughput to be come stable, usually in seconds. The streaming server measures the stabilized TCP throughput on this connection, which is then estimated as the upload capacity of the respective peer.

The maximum sending or receiving throughput along a live TCP connection is measured periodically in the following fashion: The measurement interval is further divided into 30-second sub intervals. In each sub interval, the time that is actually used to transmit media blocks is summarized, excluding the idle periods. An average throughput is calculated with the number of bytes sent in the block transmission time divided by the length of this duration. The maximum throughput is then derived as the maximum of all such average throughput within the measurement interval. Taking the average transmission throughput within 30 seconds, we smooth out the periods of very bursty TCP throughput; deriving the maximum of all such 30-second measurement, we aim to obtain the maximally achievable TCP throughput on the link
between two peers.

2.2.2 Reporting Mechanism

To dynamically monitor the entire live streaming system, we have implemented detailed measurement and reporting capabilities within the UUSee client application. Each peer collects a set of its vital statistics, and encapsulates them into “heartbeat” reports to be sent to the tracking servers every 5 minutes via UDP. The statistics include its IP address, the channel it is watching, its buffer availability map, the number of consecutive blocks in its current playback buffer (henceforth referred to as the buffering level), instantaneous aggregate download and upload throughput from and to all partners, as well as its download and upload bandwidth capacities. The download and upload capacities of a peer are estimated using measurement-based algorithms described in the previous section.

2.2.3 Trace Summary

Though we have been continuously monitoring the performance of UUSee, the study in this thesis features a most recent set of 130 GB worth of run-time traces, collected between Thursday, May 29, 2008 (GMT+8) and Monday, June 2, 2008 (GMT+8), which contain continuous-time snapshots of the streaming system throughout the period. We believe these recent traces best captured the up-to-date characteristics of peers in the millions-of-users scale, to which the application has expanded over the years. A summary of the traces is listed in Table 2.1, including a few basic statistics for all the streaming channels in the traces and for the most popular channel, CCTV News, as an example. Here, a peer session refers to the lifetime duration between the joining and the departure of a peer in a streaming channel.

Without a doubt, it is not suitable to handle such a large volume of traces with the
2.3 Survival Analysis Preliminaries

In survival analysis, the interest centers on a group or groups of individuals, for each of whom (or which) there is defined a point event, often called death or failure, occurring after a length of time called the survival time. The survival analysis represents a set of statistical methods for the analysis of failure events and involves the modeling of time to event data, e.g., the distribution of survival time in a single group, the relationship between explanatory variables and survival time, and etc.
2.3.1 Censoring

A special kind of difficulty in the analysis of survival data is the possibility that some individuals may not be observed for the full time of an experiment, in that we do not know the accurate birth and/or death times of an individual, but have only observed the time before which the individual has been born and the time after which the death occurs. Such incomplete observation of the survival time is called censoring. Note that, like failure, a censored observation is a point event and that the period of observation for censored individuals must be recorded. In survival analysis of many practical application, it often involves a specific type of censored data, grouped survival data, in that the observations for birth/failure times are made on fixed intervals, and the obtained large set of survival data features many tied survival times. Fig. 2.2 gives an illustration for such grouped censorship, in which $O_{i-2}, O_{i-1}, O_i, O_{i+1}$ are the observation times, and any failures occurred in interval $[O_i, O_{i+1})$, are all recored as $O_i$. Note that in Fig. 2.2(b), we shift birth times of all samples to $t = 0$ for survival analysis.

In the context of streaming channels, a peer’s joining represents a birth event, and its departure represents a death event. The time between its joining and departure, the peer longevity, is the survival time to be modelled. Based on our every-5-minute trace reporting mechanism, our peer longevity data derived from the traces fall into grouped survival data with 5-minute intervals.

2.3.2 Survival Function and Hazard Function

In survival analysis, a survival function is frequently used to describe the probability that an individual survives to a specific time $t$. Let random variable $T$ represent the longevity of an individual, the probability that it survives to time $t$ (after shifting birth time, as shown in Fig. 2.2(b)) is defined as:

$$S(t) = \Pr(T \geq t) = 1 - \Pr(T \leq t) = 1 - F(t),$$
where $F(t)$ is the cumulative distribution function (CDF) of the longevity $T$. Note that $S(t)$ is a monotone decreasing function with $S(0) = 1$ and $S(\infty) = \lim_{t \to \infty} S(t) = 0$.

Conversely, we can express the probability density function (PDF) of $T$ as

$$f(t) = \lim_{\Delta t \to 0^+} \frac{\Pr(t \leq T < t + \Delta t)}{\Delta t} = \frac{dF(t)}{dt} = -\frac{dS(t)}{dt}.$$  

In practice, a standard estimator of the survival function is the product-limit estimator, proposed by Kaplan and Meier [18] (also referred to as the K-M estimator). Assume there are $k$ distinct failure times $y_1, y_2, \ldots, y_k$ in ascending order such that $y_1 < y_2 < \cdots < y_i < \cdots < y_k$. Let

$$n_i = \text{the number of individuals alive just before time } y_i,$$

$$d_i = \text{the number of peers died at time } y_i.$$
The K-M estimator is then computed as follows:

\[
\hat{S}(t) = \begin{cases} 
1 & \text{if } t < y_1, \\
\prod_{i=1}^{p} \left( \frac{n_i - d_i}{n_i} \right) & \text{otherwise}, 
\end{cases}
\]

where \( p \) is determined by \( y_p \leq t < y_{p+1} \). Note that the curve of K-M estimator is a right continuous step function which steps down at each failure time \( y_i \).

A hazard function \( h(t) \), also referred to as the hazard rate, represents the instantaneous rate of failure at \( T = t \) given that the individual survived up to time \( t \). The hazard function is defined as:

\[
h(t) = \lim_{\Delta t \to 0^+} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{S(t)}. 
\]

Note that the hazard function is a rate, rather than a probability, i.e., it can assume any values in \([0, \infty)\).

Since

\[
h(t) = \frac{f(t)}{S(t)} = - \frac{dS(t)/dt}{S(t)} = - \frac{d\log(S(t))}{dt},
\]

integrating \( h(u) \) over \((0, t)\) gives the cumulative hazard function \( H(t) \):

\[
H(t) = \int_0^t h(u)du = - \log(S(t)).
\]

Thus, the relation between \( S(t) \) and \( h(t) \) is shown as follows:

\[
S(t) = \exp\left(-H(t)\right) = \exp\left(-\int_0^t h(u)du\right).
\]

2.3.3 The Cox Proportional Hazards Model

The Cox proportional hazards model [13] is a classical regression model for the analysis of censored survival time with respect to their relationship with covariates (which is the terminology in Cox modeling for influential or risk factors). It models the relationship between covariates and censored survival time based on the hazard function.
In Cox regression modeling, it models the hazard rate at time \( t \) for a session with covariate vector \( \mathbf{z} = (z_1, \ldots, z_p) \) as a function of a baseline hazard function and the risk factors. The basic Cox model is:

\[
h(t; \mathbf{z}) = h_0(t) \exp(\beta^T \mathbf{z}) = h_0(t) \exp \left( \sum_{k=1}^{p} \beta_k z_k \right)
\] (2.1)

where \( h(t; \mathbf{z}) \) is the hazard rate at time \( t \) for a session with covariate vector \( \mathbf{z} \); \( h_0(t) \) is a non-negative baseline hazard function, which is computed during the regression process; and \( \beta = [\beta_1, \ldots, \beta_p] \) is a row \( p \)-vector of coefficients corresponding to covariates in \( \mathbf{z} \).

The Cox regression based on the model in (2.1) derives the values of regression coefficients \( \beta_i, i = 1, \ldots, p \). As a probabilistic model, we can then estimate the probability that a session lasts to any specific time \( t \) (i.e., the survival function of the session), given the values of the covariates for the session.

The Cox model possesses the property that, if we look at two sessions with risk vectors \( \mathbf{z} \) and \( \mathbf{z}' \), the ratio of their hazard rates is

\[
\frac{h(t; \mathbf{z})}{h(t; \mathbf{z}')} = \frac{h_0(t) \exp(\sum_{k=1}^{p} \beta_k z_k)}{h_0(t) \exp(\sum_{k=1}^{p} \beta_k z_k')} = \exp \left( \sum_{k=1}^{p} \beta_k (z_k - z_k') \right)
\]

which is a time-independent constant. Hence, the hazard ratio of the two sessions is often called the proportional hazards model. On the other hand, this imposes the most strict restriction when applying the Cox model, because the validity of the model relies on the assumption that hazard rates for any two sessions must be in proportion all the time.

### 2.4 Existing P2P Streaming Measurements

#### 2.4.1 Trace Collection Methodologies

The trace collection is considered as the cornerstone of measurement studies. In this section, we briefly review three trace collection methods in existing literatures, and
compare them with the trace collection mechanism implemented in UUSee.

A **Passive Monitor** is usually deployed at a single node in a peer-to-peer streaming system, to record the traffic exchanged between the monitored peer and its neighboring peers [16]. A typical monitor is consist of two components: 1) a packet sniffer, e.g., tcpdump [6], which captures all inbound and outbound P2P traffic; and, 2) a packet analyzer, which extracts meaningful information from the P2P traffic. Although abound detailed information can be collected by the passive monitor from a peer’s point of view, it suffers from two major drawbacks: 1) As it is almost impossible to install packet sniffers to all of nodes in a peer-to-peer system, the passive monitor can only measure a portion of participating peers, *i.e.*, the overall performance of the entire system is missing; 2) Since most of commercial peer-to-peer streaming systems tend to use sophisticated packet format and/or cryptography to protect their private protocols, the packet analyzer sometimes cannot correctly extract the embedded information, and thus affects the accuracy and correctness of measurement results.

An **Active Crawler** is able to take full advantage of the partial membership list maintained by each peer, and recursively query online nodes in a peer-to-peer system [16]. Typically, a crawler registers itself as a peer in the system, requests a set of partners from the tracking server, and then adds them into the crawling list. For each node in the crawling list, the crawler requests for its status information and partner list, and then merges the returned partner list into the crawling list. Existing literature has shown that a good crawler can find 95% of peers for a channel within 5 seconds [16]. Though the active crawler is able to monitor a much larger set of peers than the passive monitor, it cannot obtain the detailed status of a peer, as only a few bytes of information are allowed to be exchanged between each other due to overhead concerns. Besides, active crawlers may not able to reach some peers behind NAT’s, *i.e.*, a part of peers behind NATs are not well studied.

To overcome the shortcomings of two aforementioned methods, a **Log Collection**
mechanism is implemented in the client of CoolStreaming+ [19], an experimental P2P streaming system. A dedicated log server is placed in this system, and each peer periodically reports its activities, such as user behavior events and internal status, to the log server using the HTTP protocol. The information from a peer is compacted into several parameters of the URL string. The log server stores the reports received from peers into a log file. In the log file, each log entry is a normal HTTP request URL string referred as a log string. The log string contains various number of data blocks, which are formed in “name=value” pairs and separated by “&”. Reports from peers are further divided into two classes: 1) activity reports, which are sent out immediately when the corresponding activities take place, indicate the peer activities such as joining and departure; 2) status reports, which are sent out every 5 minutes, indicate the internal state of peers. However, the design of trace collection in CoolStreaming+ cannot work very well when the system scales up. For example, there is too much overhead to send detailed status via “name=value” pairs in HTTP request, and the log server will be overwhelmed, when millions of online peers keep sending reports to it.

Different from passive monitors, active crawlers and the simple logging mechanism in CoolStreaming+, we have implemented a sophisticated and efficient trace collection component within the UUSee client, as introduced in Sec. 2.2. Our solution is able to collect vital statistics of online peer, produce compact heartbeat reports, and handle reports from millions of peers in the large-scale production peer-to-peer streaming system.

2.4.2 Measurement Results

In recent years, significant research efforts have been devoted to the measurement and improvement of peer-to-peer streaming systems. In this section, we briefly survey measurement results in the existing literature.
**Streaming Quality**

To investigate the streaming quality of peer-assisted live streaming system, Wu et al. [30] use the buffering level to objectively quantize the service quality of P2P streaming. Hei et al. [16] study the buffering level in more details by periodically harvesting peer’s buffer map. They observe that peers in PPLive seem to strive for buffer levels of 200-second media content, while only a small percentage of peers cache less than 30-second media content.

Hei et al. [16] and Li et al. [19] also consider the start-up delay in P2P streaming systems, which is defined as the time interval from when one channel is selected until actual playback starts on the screen. Using an active monitor, Hei et al. [16] record two types of start-up delays in PPLive: the delay from when one channel is selected until the streaming player pops up; and the delay from when the player pops up until the playback actually starts. In PPLive, for a popular channel the player pop-up delay is 10 to 15 seconds in general and the player buffering delay is 10 to 15 seconds, i.e., the total start-up delay is 20 – 30 seconds. It is also reported that some unpopular channels have start-up delays of up to 2 minutes.

Other than start-up delays, Hei et al. [16] and Li et al. [19] measure the playback continuity as an indicator of streaming quality. Hei et al. [16] analyze the playback statistics of various traces. They observe that the freezing probability, approximated by the ratio of the average freezing interval to the sum of the average freezing interval and average continuous interval, is relatively small; but, when freezing occurs, the average freeze interval usually exceeds 1 minute.

**Topologies and Throughput**

As P2P streaming systems are essentially overlay networks, the investigation of their topology properties have drawn attention of many networking researchers. Wu et al. [29] reveal that the stable-peer graph does exhibit small-world properties. They also
observe the overall streaming overlay may represent a low network diameter, which facilitates the quick distribution of media blocks throughout the entire topology. Li et al. [19] focus on clustering of peers behind NAT’s. They argue that peers at the edge should be able to negotiate with one another to alleviate the redundancy traffic, and the broadcast nature of local network channels should be considered.

With respect to the throughput, Silverston et al. [25], Hei et al. [16] and Li et al. [20] study the contribution level of partner. Silverston et al. rank upload/download rate of all partners of each peer, and summarize top and top ten partners. By comparing the upload/download throughput of all peers, they observe that a large amount of data are downloaded from top ten download partners, however top ten upload peers contribute a less important amount of total than download partners. Besides, the top upload and download peers only send and receive video at about 10% and 20% of the aggregate throughput, respectively. Li et al. defines a metric called contribution index, which is computed as the aggregate upload bandwidth (bytes sent) over the aggregate download bandwidth (bytes received) for each user, to capture the actual uploading contribution in a more accurate way.

Wu et al. [28] and Balakrishnan et al. [11] compare the inter/intra ISP flow throughput. They find that both inter-ISP and intra-ISP throughput distribution follows log-normal distribution. Wu et al. also show that: inter-ISP throughputs are not necessarily smaller that their intra-ISP counterparts; and, throughput asymmetry is exhibited in most of inter-ISP throughputs.

Peer Dynamics

The system population and its evolution directly reflect the scalability of a peer-to-peer system. This metric has been analyzed by several existing works [16, 29]. Wu et al. [29] discover there are around 100,000 concurrent peers at any time in a real-world commercial streaming system. There is a daily peak around 9 p.m., and a second
daily peak around 1 p.m., which identify similar daily peer number patterns as that presented in another study on PPLive [16]. Different from the weekly variance trend reported by Hei et al. [16], they observe only an unnoticeable population increase over the weekend.

To get a better understanding on whether or not a P2P system is resilient to the churn, the arrival rate and session duration distribution, are also studied in [16, 19]. Li et al. [19] reveal that the session duration follows a heavy-tailed distribution, i.e., there are some peers stay in the system for a long time and keep helping other peers. Besides, Ali et al. [9] and Hei et al. [16] reveal that download rates of peers are likely to fluctuate more significantly if their partners change too frequently. Hei et al. [16] also show that although several partners leave and several new partners arrive over a 30-second period, the average number of the changed peers in 30-second is less than 10% of the total partners, compared with the total number of partners.

With respect to measurements related to peer longevity, Stutzbach et al. [26] characterize peer arrivals and departures in three popular P2P file-sharing systems (BitTorrent, Kad and Gnutella). Hei et al. [16] characterize the distribution of peer life time in PPLive, and exhibited different life-time patterns among popular and unpopular channels. Li et al. [19] have also observed a heavy-tailed peer lifetime distribution in their measurement study of Coolstreaming. Although the observed distribution suggested the possible influence of initial watching experience, such influence was not systematically justified.
Chapter 3

Distilling Superior Peers for Popular Channels

In large-scale peer-assisted live streaming systems with a limited supply of server bandwidth, increasing the amount of upload bandwidth supplied by peers becomes critically important to the “well being” of streaming sessions in live channels. Intuitively, two types of peers are preferred to be kept up in a live session: peers that contribute a higher percentage of their upload capacities, and peers that are stable for a long period of time. The fundamental challenge is to identify, and satisfy the needs of, these types of “superior” peers in a live session, and to achieve this goal with minimum disruption to the traditional pull-based protocols that real-world live streaming protocols use.

In this chapter, based on more than 130 GB worth of run-time traces from UUSee, we wish to discover critical factors that may influence the longevity and bandwidth contribution ratio of peers in popular channels, using survival analysis techniques such as the Cox proportional hazards model and the Mantel-Haenszel test. Once these influential factors are found, they can be used to form a superiority index to distill superior peers from the general peer population. Indeed, the index can be used in any
way to favor superior peers, and we simulate the use of a simple ranking mechanism in a natural selection algorithm to show the effectiveness of the index, based on a replay of real-world traces from UUSee.

3.1 A Glance at Popular Channels in Real-World Traces

Why do we still need to refine the P2P streaming protocol while it has been deployed in such a large scale? Our first trace study, results given in Fig. 3.1, exposes an ever existing problem in real-world P2P streaming systems that we cannot ignore: unlike the theoretical expectation of unlimited scalability, the streaming quality in real-world streaming channels downgrades evidently at peak hours of the day with flash crowds of users in the channels. Here, we evaluate the streaming quality in a channel at each time as the percentage of high-quality peers in the channel, where a high-quality peer has a buffering level of more than 80% of the total size of its playback buffer. The criteria of the buffering level (i.e., the number of consecutive blocks in the playback buffer of a peer, starting from the current playback position) has been extensively used in the actual UUSee streaming protocol to evaluate the current streaming quality of a peer. Accordingly, we also use the peer buffering level as our basic streaming quality metric, based on the rationale that the more blocks a peer has cached in its buffer, the higher chance it has to enjoy a smooth playback.

The less than satisfactory streaming performance with an increasing number of peers — mainly ascribed to breaching the sustainable threshold of limited server bandwidth — confirms our supposition on the yet-to-improve scalability and stability of large-scale P2P streaming systems, which constitute the ultimate goal of study in this thesis. To promote peer online times for stable bandwidth supplies, we explore critical factors that influence the peer longevity; to increase the amount of peer bandwidth supplies for better scalability, we investigate what we can do to improve the percent-
3.2 Peer Longevity: Hazard Regression Modeling

In this section, we investigate the influence of various factors on peer longevity in popular P2P streaming channels, using survival analysis techniques. We first explore the critical influential factors by survival curve plotting and correlation study, and then derive a Cox proportional hazards model to describe the relationship between peer longevity and its influential factors.

3.2.1 Exploring Risk Factors

In order to discover useful insights to improve peer stability, we now seek to investigate potential factors that influence the peer longevity, and choose critical ones as the risk factors for Cox regression model.
Chapter 3. Distilling Superior Peers for Popular Channels

Streaming Quality

Intuitively, unfavorable streaming quality, to some extent, may result in the premature departure of peers. Therefore, we start by investigating: Do peer longevity patterns differ significantly under different levels of streaming quality? To answer this question, we categorize peer sessions according to the average buffering level achieved throughout each session, and plot the survival curves, namely the survival function estimated using the K-M algorithm, of the different groups. Fig. 3.2 shows the survival curves for three session groups with the average buffering level in the ranges of 0 − 25%, 25 − 75% and 75 − 100% of the total buffer size (500 media blocks), respectively. We can observe significant differences across the survival curves, that the session duration is generally larger when the streaming quality is better. We further statistically validate our observations using the Mantel-Haenszel test [22], also referred to as the log-rank test. The log-rank test is commonly applied to test the null hypothesis that a set of survival functions are statistically equivalent, in which the null hypothesis is rejected if the result p-value is lower than the significance level of 0.05. We have derived a log-rank test result of $p = 1 - \Pr_{\chi^2,2}(14755) \approx 0$, which confirms the significance of the differences among the survival functions for the three groups.

Not satisfied by only revealing the relevance between the streaming quality and session duration, we take one step further to explore the best statistical metrics of the streaming quality, that represents the most correlation with the session duration. The factors to be compared are: the average buffering level during a peer session, the standard deviation of the buffering level throughout a peer session, the minimum buffering level during a peer session, and the initial buffering level, as the first buffering level measured when a peer starts its playback. In Fig. 3.3 − 3.6, we plot the average and median session durations of each session group at different levels of the respective streaming quality factor, as well as the smoothed Lowess curves [12].

Fig. 3.3 generally reveals a positive correlation between the session duration and
Figure 3.2: Survival curves for sessions with three different levels of streaming quality: 0 – 25%, 25 – 75% and 75 – 100%.

The average buffering level, but it is only apparent above a certain threshold value around 225 – 250 for both curves. We also notice that the curves slightly drop in the last range of the buffering level, 475 – 500, which may further reveal the difficulty to maintain a near-full buffer in long streaming sessions, while a slightly less full buffer can already guarantee a smooth viewing experience to keep the peers staying longer.

The negative correlation between the standard deviation of buffering level and session duration, as shown in Fig. 3.4, meets our expectation that the less stable the streaming quality is, the shorter the peers are staying. However, the smoothed curve of averaged values does not match that of median values very well, i.e., the correlation is not strong and consistent enough for us to select the standard deviation as the best risk factor to decide session duration.

We further investigate the tolerance of peers towards the lowest possible streaming quality, by plotting the correlations with respect to the minimum buffering level, in Fig. 3.5. No dominant correlation is observed in Fig. 3.5, revealing that the minimum buffering level metric is not suitable for our purpose as well.

On the other hand, we investigate the effects of initial streaming quality towards the peer longevity, by plotting the correlations with respect to initial buffering level
Figure 3.3: Correlation of session duration with the average buffering level during a peer session.

Figure 3.4: Correlation of session duration with the standard deviation of the buffering level throughout a peer session.

Figure 3.5: Correlation of session duration with the minimum buffering level during a peer session.
of a session in Fig. 3.6. A strong and consistent positive correlation is observed between the session duration and initial buffering level in Fig. 3.6, with respect to both the median and average curves. We further check such linear correlation by computing Pearson’s correlation coefficients [14]; and with the results showing 0.96 and 0.98 for the mean and median respectively, an extremely strong positive linear correlation is suggested. This observation represents the first interesting discovery in our study that, out of the many possible streaming quality factors, the streaming quality experienced by a peer at the beginning stage of its playback critically influences the interest of a peer in a streaming channel, regardless of any original interest towards the possible content of the channel.

**Joining Time**

Other than the streaming quality, we expect the time when a peer surfs the Internet also influences its viewing behavior. To investigate how significant the effect of the time is, we categorize the peer sessions according to their start times and compare the survival functions of the resulting session groups.

We first explore any possible effect of the day of the week, using sessions starting at a same time on a weekday, Thursday May 29, and on the weekend, Saturday May 31.
Fig. 3.7 exhibits no significant difference between the two session groups, no matter whether the start time is in the morning (10 a.m.) or in the evening (10 p.m.). In addition, the results of log-rank tests, $p = 1 - \Pr_{\chi^2,1}(2.3) \approx 0.06 > 0.05$ and $p = 1 - \Pr_{\chi^2,1}(2.1) \approx 0.07 > 0.05$ for the 10 a.m. and 10 p.m. cases, confirm our observations that there is no significant statistical difference between the two survival functions, respectively.

Nevertheless, when we zoom into different times on a same day and classify sessions according to the hours they start, the effect of time becomes more evident. Fig. 3.8 exhibits visible differences among survival curves for session groups of four different starting times on May 30: 15.3% of the peers starting around 10 p.m. stay for more than an hour, while only 10% of those starting around 10 a.m. have such a longevity. The log-rank test results of $p = 1 - \Pr_{\chi^2,3}(20.7) \approx 0$, rejects the null hypothesis that survival functions are equivalent and validates our observations.

In addition, we have investigated the differences among survival curves of other times of the day and among different days. The similar log-rank test results further confirm our second interesting discovery: the peer joining time during one day’s
HARTER 3. DISTILLING SUPERIOR PEERS FOR POPULAR CHANNELS

Figure 3.8: Survival curves for sessions starting at different times of a day.

course significantly decides how long it can stay, e.g., peers can afford to watch the streaming channels longer at their evening leisure times; instead, the expected day of the week effect, that peers may stay longer during the weekend, turns out not to be important.

Channel Popularity

We next investigate whether peer longevity may differ significantly across channels of different popularity, by plotting the correlation between channel population and average session duration across all of the 800 streaming channels in Fig. 3.9. Each sample in the figures represents one streaming channel. The population of each channel is computed as the average concurrent number of peers in the channel over the trace period. To eliminate the time effect, the average session duration for each channel is evaluated using peer sessions in the channel, which start within one specific hour, e.g., 9 a.m. and 9 p.m. on May 30, as shown in the figures respectively.

Fig. 3.9 exhibits an evident positive linear correlation between the two quantities at the log-log scale, i.e., the more popular a channel is, the longer the peers may stay.
Figure 3.9: Correlation between channel population and average longevity in log-log scale, with the linear fitting line and 95% confidence intervals.

We have computed the Pearson’s product-moment correlation coefficients, and the \( p \)-values for testing the null hypothesis that there is no significant correlation between the two quantities. Both the Pearson’s coefficients which gives 0.762 and 0.695 for 9 a.m. and 9 p.m. respectively, and \( p \)-values that are extremely close to zero, further validate the significance of the correlation. Therefore, the channel popularity is identified as the third important risk factor to decide peer longevity.

### 3.2.2 Regression Modeling

With three important influential factors identified, we now seek to model the peer longevity as a function of these factors, using the regression techniques in survival analysis.

**The Cox Regression Model**

As described in Sec. 2.3, the basic Cox model is:

\[
h(t; \mathbf{z}) = h_0(t) \exp(\beta^T \mathbf{z}) = h_0(t) \exp(\sum_{k=1}^{p} \beta_k z_k)
\]  
(3.1)
where \( h(t; z) \) is the hazard rate at time \( t \) for a session with covariate vector \( z \); \( h_0(t) \) is an arbitrary non-negative baseline hazard function, which is computed during the regression process; and \( \beta = (\beta_1, \ldots, \beta_p) \) is a column \( p \)-vector of coefficients corresponding to the covariates in \( z \). In our regression modeling, the covariates are selected corresponding to the influential factors on peer longevity we have observed in the previous section: one continuous variable, BUF, is used to represent initial buffering level at the peer. Another continuous variable, POP, corresponds to the population of the channel the peer is in. To represent the time of day effect of peer joins, we divide the time in a day to 24 intervals, each corresponding to one hour, and use 24 indicator variables, \( \text{TOD}_i, i = 0, \ldots, 23 \), to denote the joining time of a peer. For example, if the peer joins its channel between 9 a.m. and 10 a.m., we have \( \text{TOD}_9 = 1 \) and \( \text{TOD}_i = 0, \forall i \in \{0, \ldots, 23\} \setminus \{9\} \). The covariates, along with their description and type, are listed in Table 3.1. Altogether, a covariate vector with \( p = 26 \) components is used in our Cox regression.

**Table 3.1: Covariates in Cox Regression Model**

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>BUF</td>
<td>Initial buffering level</td>
<td>Continues</td>
</tr>
<tr>
<td>POP</td>
<td>Channel population</td>
<td>Continues</td>
</tr>
<tr>
<td>( \text{TOD}_i, i = 0, \ldots, 23 )</td>
<td>Joining time of the day</td>
<td>Binary</td>
</tr>
</tbody>
</table>

The Cox regression based on the model in (3.1) derives the values of regression coefficients \( \beta_i, i = 1, \ldots, p \). As a probabilistic model, we can then estimate the probability that a session lasts to any specific time \( t \) (i.e., the survival curve of the session), given the values of the covariates for the session and using the derived coefficients. In the following section, we first discuss how we estimate \( \beta \), and then we show how the derived Cox model can be used in the estimation of session duration in the following part of this section.
Maximum Likelihood Estimation

To derive the regression coefficients in the Cox model in Equation (3.1) based on our large sets of grouped survival times, i.e., the peer session durations derived from the every-five-minute traces, we employ a maximum likelihood estimation algorithm similar to that proposed by Prentice et al. [24] for grouped data version of the Cox model. In this model, peer session durations are grouped into intervals \( A_i = [a_{i-1}, a_i), i = 1, \ldots, r \) with \( a_0 = 0, a_r = \infty \). Assuming all sessions start at \( a_0 \), the durations of sessions ended in \( A_i \) are all recorded as \( t_i \). From (3.1), the probability of observing a session duration \( t_i \) on a peer session with covariate vector \( z \) is

\[
1 - \alpha_i \exp (\beta^T z) \prod_{j=1}^{i-1} \alpha_j \exp (\beta^T z) 
\]

(3.2)

where

\[
\alpha_j = \exp \left( - \int_{a_{j-1}}^{a_j} h_0(u) du \right)
\]

is the conditional survival probability in \( A_j \) for an individual with \( z = 0 \). The likelihood function of the regression model in (3.1) is the product of terms (3.2) over all the peer sessions in the traces.

Let \( \gamma_j = \log(-\log \alpha_j) \). The logarithm of the likelihood contribution from each session, as in (3.2), can be written as

\[
l = \log \left( 1 - \exp \left( - \exp (\gamma_k + \beta^T z) \right) \right) - \sum_{j=1}^{k-1} \exp (\gamma_j + \beta^T z).
\]

(3.3)

In this way, the original Cox regression problem is converted to a maximum likelihood estimation (MLE) problem [15], in which we estimate the parameters \((\hat{\gamma}, \hat{\beta})\) that maximize the likelihood represented as the sum of terms (3.3) over all the peer sessions, based on the data of their session durations and risk factor values. To carry out
the maximum likelihood estimation, the Newton-Raphson approach \[17\] can be easily applied.

In Table 3.2, we present the results of maximum likelihood estimation, using data from 231570 sessions in our traces. The sessions used are from 20 channels randomly selected from popular channels in the traces. The purpose for such sampling is not only to expedite the speed of maximum likelihood estimation, but also to exhibit the usefulness of our model, trained using only a limited set of samples, as is to be illustrated in the following section. We have chosen to show the estimated values of selected components of $\hat{\beta}$ and $\hat{\gamma}$, along with their standard errors. Note that the maximum index of $\hat{\gamma}$ is decided by dividing the maximum session duration from the traces by the trace collection interval of 5 minutes. The negative $\hat{\beta}$ values corresponding to BUF and POP validate our earlier observations on their positive effects on the session duration: the higher the initial buffering level is and the more popular the respective channel is, the lower the failure probability of a peer session is, and thus the session duration could be longer. Although the $p$-value for each $\hat{\beta}$ is not given in the table, all $p$-values are far below 0.05, suggesting all covariates are significant.

Table 3.2: Maximum Likelihood Fit of Cox Regression Model in (3.1)

<table>
<thead>
<tr>
<th>Covariate</th>
<th>$\hat{\beta}$</th>
<th>Std. Err.</th>
<th>Intervals</th>
<th>$\hat{\gamma}$</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>BUF</td>
<td>-0.0310</td>
<td>1.19e-07</td>
<td>0–1</td>
<td>-0.2953</td>
<td>1.13e-04</td>
</tr>
<tr>
<td>POP</td>
<td>-0.2787</td>
<td>1.53e-05</td>
<td>2–3</td>
<td>-1.3747</td>
<td>1.62e-04</td>
</tr>
<tr>
<td>TOD$_0$</td>
<td>0.8034</td>
<td>4.45e-04</td>
<td>4–5</td>
<td>-1.5993</td>
<td>1.95e-04</td>
</tr>
<tr>
<td>TOD$_4$</td>
<td>0.0586</td>
<td>1.05e-03</td>
<td>6–7</td>
<td>-1.7477</td>
<td>2.40e-04</td>
</tr>
<tr>
<td>TOD$_8$</td>
<td>0.4421</td>
<td>3.57e-04</td>
<td>8–9</td>
<td>-1.6648</td>
<td>2.58e-04</td>
</tr>
<tr>
<td>TOD$_{12}$</td>
<td>0.6915</td>
<td>3.02e-04</td>
<td>10–11</td>
<td>-1.7799</td>
<td>3.13e-04</td>
</tr>
<tr>
<td>TOD$_{16}$</td>
<td>0.7540</td>
<td>3.40e-04</td>
<td>12–13</td>
<td>-1.7433</td>
<td>3.49e-04</td>
</tr>
<tr>
<td>TOD$_{20}$</td>
<td>0.7000</td>
<td>3.11e-04</td>
<td>14–15</td>
<td>-1.8224</td>
<td>4.22e-04</td>
</tr>
</tbody>
</table>
The use of the Cox regression model is based on a presumed proportional hazards assumption [13], that the ratio of the hazard rates of two sessions is only dependent on their covariate values, but independent of time. As a check on the proportional hazards assumption, we apply the likelihood ratio test [27]. The result of the test gives a very small $\chi^2$ value of 376 on 26 d.f., which is far below the 0.05 significance level. Therefore, the proportional hazards assumption stands, and the appropriateness of using the Cox regression model with the covariates in Table 4.1 is confirmed.

**Longevity Prediction and Model Validation**

With the Cox regression model established, we can now derive the survival curve of a session with covariate vector $z$. For the grouped Cox model, the estimator of the survival function with covariate vector $z$ at time $t_k$ can be written as:

$$\hat{S}(t_k; z) = \prod_{j=1}^{k-1} \exp \left( - \exp(\hat{\gamma}_j + \hat{\beta}^T z) \right).$$

We use the expected session time in the survival curve of a session with $z$, as the most probable session duration of the session. In this way, given a covariate vector $z$, we are able to predict the most probable session duration using our Cox regression model.

Recall that our regression model is trained using only a limited set of session data from 20 random popular channels. We now evaluate its accuracy in estimating the duration of sessions from other channels, with representative results in Fig. 3.10.

Fig. 3.10 plots the measured median durations, along with the predicted durations in highlighted (solid) curves, of peer sessions at different levels of initial buffering level (BUF), with four different cases of POP and TOD: Fig. 3.10(a) and (b) plot sessions started around 10 p.m. ($TOD_{22} = 1$), in a very popular channel ($POP = 3162$) and in a less popular channel ($POP = 851$), respectively; and Fig. 3.10(c) and (d) plot sessions in the same channel (with $POP = 932$), starting at 10 a.m. ($TOD_{10} = 1$) and 10 p.m. ($TOD_{22} = 1$), respectively. Predictions in all four figures fall into the 75%
confidence intervals (in dash lines), which validates the usefulness of our regression model — derived using a small portion of session data — in the accurate prediction of session durations in the entire traces. The peer longevity model derived in this section provides a useful tool for the estimation and promotion of peer session duration in P2P streaming, in order to enhance the stability and eventually the streaming quality in the system. Practically, we may only be interested in promoting the longevity of high-value peers, i.e., the ones who can contribute a high level of upload bandwidth. A question arises: how can we decide, especially at the early stage after peer joins, which peer can contribute significantly throughout its session time? In the following section, we seek to find the answer to this question.

Figure 3.10: Regression model validation by prediction of the peer longevity.
3.3 Bandwidth Contribution Ratio: Influential Factors

Intuitively, a peer may upload more when it inherently has a large upload capacity, e.g., the case of an Ethernet peer. Nevertheless, it is not necessarily so that a peer is always able to contribute all its upload bandwidth for streaming. In seeking the causes, we do not consider the selfishness of peers, as none of the well-known real-world P2P streaming applications implement any mechanism allowing peers to decide its bandwidth contribution level; we also exclude the possibility of significant protocol inefficiency in UUSee P2P streaming, based on our knowledge of its elaborated peer selection and NAT/firewall traverse algorithms implemented to maximize peer bandwidth utilization. Indeed, our focus is on the “objective” factors, such as the network condition and the streaming quality, that may have led to low levels of peer bandwidth contribution. Considering most ISPs in China confine the upload capacity to 512 Kbps, we define 512 Kbps as the threshold capacity in this thesis, and introduce the bandwidth contribution ratio, the ratio of contributed bandwidth at a peer over the threshold capacity, to measure the normalized upload bandwidth utilization in the P2P system. Note that in special cases where the ratio is greater than 1, they are considered as 1 for the convenience of our study. In this section, we seek to explore the important factors that decide the average bandwidth contribution ratio over a session’s course, in order to derive useful insights to identify potential high-contribution peers using the combination of the ratio and upload capacity of each peer.

3.3.1 Peer Longevity

Long-lived peers, who are online for a long period of time, are generally regarded as superior peers, not only due to their stability, but also based on a hidden assumption: those stable peers may contribute more of their upload capacity to the P2P streaming. But is this assumption true? To investigate this question, we plot in Fig. 3.11 the
average and median bandwidth contribution ratios of sessions at different levels of the session duration, as well as the smoothed Lowess curves. The bandwidth contribution ratio of each session is computed by dividing the average upload bandwidth of the peer during the session, whose measurement methodology was mentioned in Sec. 2.2, by the threshold capacity of 512 Kbps. No significant correlation has been observed in Fig. 3.11, which suggests long session duration and high bandwidth contribution level do not necessarily happen altogether at the same peers, and also turns away peer longevity from our influential factor candidate set.

![Figure 3.11: Correlation of bandwidth contribution ratio with session duration.](image1)

Figure 3.11: Correlation of bandwidth contribution ratio with session duration.

![Figure 3.12: Correlation of bandwidth contribution ratio with the average buffering level during a peer session.](image2)

Figure 3.12: Correlation of bandwidth contribution ratio with the average buffering level during a peer session.

We now turn to factors that may fundamentally limit the upload ability of a peer,
e.g., low buffering level that represents a limited number of blocks to serve other peers, or inter-peer bandwidth bottlenecks that prohibit the full utilization of last-mile capacities.

### 3.3.2 Streaming Quality

We first investigate the effect of buffering level on the bandwidth contribution ratio of a peer. Fig. 3.12 plots the average and median bandwidth contribution ratios of session groups at different levels of streaming quality, in terms of the average buffering level throughout the session duration. A positive correlation can be observed in both plots, confirming our guess on the impact of peer buffering level on the utilization of its upload capacity. Similar to Fig. 3.3, which reveals a threshold effect around 250, the correlation in Fig. 3.12 is more evident when the average buffering level is beyond a threshold value around 225 – 250.

![Figure 3.13: Correlation of bandwidth contribution ratio with the initial buffering level.](image)

On the other hand, Fig. 3.13, which plots the relationship between bandwidth contribution ratio and the initial buffering level of the sessions, reveals a stronger linear positive correlation between bandwidth contribution ratio and the initial buffering level, with respect to both the median and average curves. This surprising observa-
tion, that the initial buffering level of a peer session exhibits better correlation with the average bandwidth contribution ratio throughout the session, other than the average buffering level, represents an interesting discovery in our study, which works in favor of us: the average bandwidth contribution level of a peer during its lifetime may be quite accurately predicated using its initial streaming quality upon joining, such that a number of measures can be taken immediately to favor those high-contribution peers.

### 3.3.3 ISP Membership

We next investigate any bottleneck effect on the inter-peer links, that may limit the utilization of the last-mile capacities at the peers. Our previous study in [28] has revealed the existence of bandwidth bottlenecks along inter-ISP P2P links in UUSee P2P streaming network. Considering that peers in larger ISPs have a higher percentage of intra-ISP links while peers in small ISPs may mostly connect to partners in other ISPs, we wonder whether the achievable bandwidth utilization ratios represent any difference among peers in ISPs of different sizes. To investigate this issue, we categorize peer sessions according to their ISP membership, and compare the bandwidth contribution ratios of different session groups. As we have identified the significant impact of initial buffering level on the ratio, we plot the correlation of average bandwidth contribution ratio and initial buffering level for each session group respectively, and compare the resulting plots in Fig. 3.14. In each of the figures, we not only show the smoothed Lowess curves, but also plot the fitted linear regression line (in dash) of the average bandwidth contribution ratios at different levels of initial buffering level. The ISP each session group corresponds to is marked at the upper-left corner. Note that the ISPs are listed in the descending order of their peer population. Statistics from the linear regression analysis of each figure are given in Table 3.3.

From Table 3.3, we observe small values of the slopes for the regression lines in Fig. 3.14, due to the large difference in the magnitudes of bandwidth contribution ra-
Figure 3.14: Correlation of bandwidth contribution ratio with initial buffering level in different ISPs.

tios and buffering levels. Nevertheless, the positive correlation coefficients, together with the near-0 \( p \)-values, validate the significance of the slopes, and also confirm the significance of the correlation between initial buffering level and bandwidth contribution ratio in the cases of each ISP. The most interesting observation we can make from Fig. 3.14 and Table 3.3 is: the slope of the regression line is steeper for ISPs of a larger size, and is flatter in the cases of smaller ISPs. In another word, at a same initial buffering level, peers in larger ISPs may have a higher bandwidth contribution ratio than those in smaller ISPs. Considering peers in larger ISPs may have more neighbors in the same ISPs than those in small ISPs, such an observation can be explained by the less impact of inter-ISP bandwidth bottleneck on the upload capacity utilization at peers in larger ISPs than those in small ISPs. This represents another interesting discovery in our study of influential factors to bandwidth contribution ratio, that the ISP membership of a peer also decides its ability to utilize its upload capacity, which
we may also make use of in the selection of high-contribution peers.

### 3.4 Superiority Index: A Simple Peer Ranking Mechanism

The regression model for peer longevity and influential factors to the bandwidth contribution ratio bring useful insights towards the improvement of stability and scalability of large-scale P2P streaming systems. As an important application, we propose a Superiority Index, for distilling superior peers during streaming, which can potentially stay in the system for a long time and contribute a high level of upload bandwidth. The index is defined in the following fashion:

\[
Superiority \text{ Index} = \text{Predicted Peer Longevity} \times \text{Estimated Average Upload Bandwidth}
\]

As the product of estimated peer session duration and average upload bandwidth during the session, the Superiority Index estimates the potential overall bandwidth contribution at a peer during its session time. Such a Superiority Index can be used to design a simple ranking mechanism in a natural peer selection algorithm, that augments the current P2P streaming protocol, as follows.
In a P2P streaming protocol such as UUSee, new peers connect to a set of existing peers randomly assigned by the tracking server, and each existing peer would treat all new connected peers equivalently and divide its upload bandwidth among them. In our proposed natural selection algorithm, after each new peer has connected and obtained its initial streaming bandwidth, the upstream peer will decide on the potential contribution of the peer by computing its Superiority Index; it then ranks all the new peers connected to itself by their superior indices, and only those peers with large superior indices are kept as the neighbors, while those with small index values will be disconnected. The rationale behind this peer selection process is that, given the limited upload bandwidth in the system, we may only wish to keep the superior peers with potentially better stability and upload bandwidth contribution, and cut off inferior peers as soon as possible, for better stability and scalability of the entire system.

In computing the Superiority Index of each peer, the peer longevity is predicated using the Cox regression model we derived in Sec. 3.2.2, based on the initial buffering level the peer has experienced, the channel it is in and its joining time of the day. The average upload bandwidth is estimated by multiplying the bandwidth contribution ratio we discussed in Sec. 3.3, with the threshold capacity of 512 Kbps if the peer is an ADSL peer (as in China the upload capacity of a major portion of ADSL peers are limited to 512 Kbps by ISPs), or with the total upload capacity of the peer in the case of Ethernet peers. The bandwidth contribution ratio of a peer can be derived using its ISP membership and initial buffering level, based on the linear relationships we have derived Sec. 3.3 between the ratio and the initial buffering level in each ISP.

To evaluate the effectiveness of the Superiority Index in distilling superior peer and promoting the “well-being” of the streaming system, we have implemented the natural selection algorithm in a P2P streaming system, that emulates UUSee protocols and replays the real-world scenarios captured by the traces. In our experiments, we
emulate the streaming of channel CCTV1 over one day’s course with the same number and ISP distribution of participating peers, as captured in the traces of May 30, 2008. We also emulate peer dynamics by having peers join and depart from the channel following the peer arrival times and session durations derived from the traces. The upload and download capacities of each peer are generated according to their respective distributions summarized from the traces as well.

![Figure 3.15: The evolution of channel population in the simulation.](image)

(a) Without natural selection algorithm  
(b) With natural selection algorithm

![Figure 3.16: Streaming quality in the system with and without natural selection algorithm.](image)

In our experiments, we run the P2P streaming system without and with the natural selection in place, and compare the average streaming quality in the channel achieved over time. Given the evolution of the peer population in the channel shown in Fig. 3.15, Fig. 3.16(a) and Fig. 3.16(b) plot the achieved average streaming qual-
Figure 3.17: Comparison of streaming quality with and without the natural selection (NS) algorithm, during the time period 18:00 – 24:00.

Figure 3.18: Comparison of streaming performance with and without the natural selection (NS) algorithm.

In addition, Fig. 3.18 plots the aggregate upload bandwidth of peers in the streaming channel during the peak hours, in the cases with and without the natural selection. We can see the aggregate bandwidth contribution in the system with the natural selec-
tion is generally larger than that without it, due to the promotion of high bandwidth peers in the system.

All the above observations exhibit the effectiveness of the proposed superiority index in a natural selection algorithm, which effectively promotes the session duration of high contribution peers, thus enhancing the overall streaming quality in the P2P streaming system.

3.5 Summary

In this chapter, we discover the influential factors to peer longevity and bandwidth contribution level in a practical large-scale P2P streaming application, UUSee. We have identified and modeled the key influential factors that decide the duration of peer sessions, using survival analysis techniques. With respect to the bandwidth contribution ratio at each peer, we have identified the impact of the peer initial buffering level and ISP membership, and developed a linear model to represent their correlations. To apply our discoveries into real-world applications, we design a superiority index for distilling superior peers from the general peer population. Such index is used in a natural selection algorithm to promote the session duration of high contribution peers. Our simulation shows the effectiveness of this superiority index in improving the overall stability and scalability of the P2P streaming system.
Chapter 4

Deciphering Peer Instability in Unpopular Channels

In the real-world peer-assisted live streaming systems with a large number of concurrent channels, practical experiences have revealed the unbalanced distribution of peers across different channels: in a popular channel, there may be thousands of concurrent online users, while in an unpopular channel there is no more than a few hundred of peers. It must be noted that these small unpopular channels, which generally represent the majority of the available channels in the streaming system, usually experience lower streaming quality, as compared to large popular channels. In contrast to the previous chapter, which put efforts to guarantee the performance of popular channels, \textit{i.e.}, to accommodate a flash crowd scenario where a large number of peers join in a short period of time, in this chapter we pay our attention to the improvement of streaming quality in unpopular channels.

Focusing on unpopular channels in large-scale P2P streaming systems, we have investigated the distribution of peer population and streaming quality across different channels from the UUSee’s real-world traces, and observed inferior streaming qualities that are empirically experienced by unpopular channels. We have further dis-
covered a short peer longevity (severe peer volatility) in unpopular channels, which reveals a less than desirable situation that may lead to a downward spiral of peer population: On one hand, the low streaming quality in an unpopular channel may lead to short peer stay in the channel; on the other hand, the more severe peer churn further exacerbates the streaming quality of existing peers. To promote peer stability for a better streaming quality, it is critical to thoroughly understand and characterize the important factors that may have caused the peer volatility in unpopular channels.

Towards this objective, we conduct a comprehensive and in-depth statistical analysis using the UUSee traces. Our goal is to identify critical performance metrics as risk factors that may influence the lifespan of peers, in order to derive useful insights towards the improvement of stability of peers in unpopular channels.

### 4.1 Observations on Unpopular Channels

Why do we need to investigate the streaming performance in small channels and large channels distinctively in such a large-scale system? First of all, Fig. 4.1 plots the distribution of concurrent peer population in different streaming channels in UUSee, as computed as the average simultaneous number in each channel in the traces. We can see the popularity differs significantly across channels, with a small number of most popular channels (≈ 2%) with an average peer population of more than 5000, a small percentage of channels (≈ 31%) with a population in the range of 500 to 5000, and the majority of UUSee channels accommodate a peer population with less than 500 peers (≈ 67%). Fig. 4.2 plots the correlation between the streaming quality and peer population in all UUSee channels in two representative snapshots, 9 a.m. on May 30 and 9 p.m. on May 30. Here, we evaluate the streaming quality in a channel at each time as the percentage of high-quality peers in the channel, where a high-quality peer has a buffering level of more than 80% of the total size of its playback buffer (buffer size
in UUSee is 500 media blocks). The criterion of the buffering level (i.e., the number of consecutive blocks in the playback buffer of a peer, starting from the current playback position) has been extensively used in the actual UUSee streaming protocol to evaluate the current streaming quality of a peer. Accordingly, we also use the peer buffering level as our basic streaming quality metric, based on the rationale that the more blocks a peer has cached in its buffer, the higher chance it has to enjoy a smooth playback. We can observe from Fig. 4.2 that small channels generally represent worse streaming quality, as compared to large popular channels. The less than satisfactory streaming performance in small channels — which represent the majority of stream-
ing channels in UUSee — expose a critical challenge in improving the performance of real-world streaming systems: How shall we boost the streaming quality of small unpopular channels?

In P2P streaming systems, peer instability represents a killer factor hindering the achievable streaming quality. It is even true to small channels, as evidenced by our trace studies in Fig. 4.3 and Fig. 4.4. We observe that the peer longevity tends to be shorter in the small channels from Fig. 4.3, while in most cases the more severe peer churns further exacerbate the streaming quality in those channels, as shown in Fig. 4.4. All these observations have pointed to the following fact: To promote the

![Figure 4.3](image1.png)

**Figure 4.3:** Correlation between channel population and peer longevity.

![Figure 4.4](image2.png)

**Figure 4.4:** Correlation between peer longevity and streaming quality.
streaming quality in small channels, a key step is to enhance the stability in these channels, by promoting peer online times for more stable bandwidth contribution. In order to promote peer stability, we identify it important to obtain a thorough and in-depth understanding of the critical factors that influence the peer online times in the streaming channels, which constitutes the major objective of study in this chapter.

4.2 Peer Instability: Influential Factors

In this section, we investigate the influence of various factors on peer longevity in unpopular P2P streaming channels, using survival analysis techniques, such as correlation studies and survival curve plotting.

4.2.1 Buffering Level

Intuitively, the higher buffering level a peer experiences, the smoother its streaming is, and the more likely it will stay longer in the channel. Therefore, we start by investigating: Do peer longevity patterns differ significantly under different buffering levels? To answer this question, we explore the relevance between peer longevity and various statistical metrics of the buffering level, including the average buffering level during a peer session, the standard deviation of the buffering level throughout a peer session and the initial buffering level, as the first buffering level measured when a peer starts its playback. As a statistics to represent the distribution of peer longevity among a group of sessions, we define an EDR\( (t) \) function, i.e., Early Departure Rate function, as the percentage of peers whose lifespan is less than or equal to \( t \) minutes within a group. In Fig. 4.5 – Fig. 4.7, we plot the EDR\( (15 \text{ min}) \) of each session group categorized according to different levels of the respective buffering level metric, as well as the smoothed Lowess curves. Note that in all our studies hereinafter, we use peer session data from all the unpopular channels, i.e., channels with less than 500 peers most
of the time, in order to derive insights useful for their performance enhancement.

![Graph](image1.png)

Figure 4.5: Correlation of EDR function with the average buffering level during a peer session.

![Graph](image2.png)

Figure 4.6: Correlation of EDR function with the standard deviation of the buffering level throughout a peer session.

Fig. 4.5 reveals a negative correlation between the early departure rate and the average buffering level within the buffering level range of $200 - 475$, showing that the departure rate is higher (peer lifespan is shorter) when the average buffering level is lower in this majority range. The positive correlation between the standard deviation of buffering level and early departure rate, as shown in Fig. 4.6, meets our expectation that the less stable the buffering level is, the shorter the peers are staying.

We further investigate the tolerance of peers towards the initial buffering level, by plotting the correlations in Fig. 4.7. A strong negative correlation is observed in Fig. 4.7
between the early departure rate and initial buffering level within the buffering level range of 0 – 120 and 320 – 500, respectively. This reveals that at the two ends of the spectrum, an excellent initial buffering level brings a longer peer online time, and a very poor initial buffering level will almost definitely result in an early departure. In our study, we have varied $t$ in the $\text{EDR}(t)$ function from 5 minutes to 60 minutes, and made similar observations.

### 4.2.2 Peer Incoming Degree

In P2P streaming, the number of supplying peers a peer can obtain in a streaming channel, *i.e.* its incoming degree or indegree, and how stable these incoming connections are, affect the streaming quality it obtains, and thus affect the longevity of the peer in the channel. To investigate such impact of peer indegree, we plot in Fig. 4.8 and Fig. 4.9 the $\text{EDR}(15 \text{ min})$ values of session groups at different levels of the average indegree during a peer session and the standard deviation of the indegree throughout a peer session, respectively.

Fig. 4.8 shows an interesting phenomenon: When the peer indegree is at a smaller value ($< 20$), a negative correlation exists between the average indegree and the early departure rate, meaning that the more suppliers a peer has, the longer it may stay;
however, when the indegree goes up, a positive correlation result, showing that the
departure rate is high even when peers know many others in the same channel. To explain the latter part of the observation, we have further observed that the majority of peers in unpopular channels in UUSee have an indegree lower than 30, and only a few may have large indegree up to one hundred. Interesting enough, the peers with large indegrees are generally those with poor buffering levels, which thus strive to find more possible suppliers, but are nevertheless unable to get a satisfactory streaming quality.

Fig. 4.9 plots a positive correlation between the standard deviation of indegree and
the early departure rate. This reveals the following: when the number of incoming connection fluctuates significantly at a peer, the peer may not be experiencing smooth streaming, and thus is more prone to early departure.

### 4.2.3 Time Effects

Intuitively, the time when a peer surfs the Internet also influences its viewing behavior. We then explore any possible effect of the time of the day, using sessions starting at different times on a same day and classify sessions according to the hours they start. Fig. 4.10 exhibits visible differences among survival curves for session groups of four different starting times on May 30. We further statistically validate our observations using the Mantel-Haenszel log-rank test. The log-rank test result of \( p \approx 0 \), rejects the null hypothesis that survival functions are equivalent and validates our observations.

![Figure 4.10: Detecting the time of the day effect in unpopular channels.](image)

### 4.2.4 Last-Mile Link Type

We next investigate the possible difference in peer longevity among peers with different last-mile link type. The majority of UUSee peers are in China, where two dominant types of Internet connections, Ethernet and ADSL, provide users different bandwidths and connection stability: 1) Most Ethernet users are provided with a download and
upload bandwidths around 10 Mbps, while ADSL users typically have a download bandwidth around 1 Mbps and an upload bandwidth no more than 512 Kbps; 2) Ethernet users usually connect to fiber optic routers located in the same building with much more stable connections than those of ADSL users, whose stability largely depends on the quality of telephone circuits. Our trace study has revealed that 54% and 46% of UUSee peers are ADSL and Ethernet users, respectively. These differences between Ethernet and ADSL connections have motivated us to explore their possible effects on peer longevity in unpopular channels.

![Figure 4.11: Survival curves for peer sessions of different last-mile link types.](image)

We categorize peer sessions according to their last-mile type, and compare the survival functions of the resulting groups, as plotted in Fig. 4.11. Evident difference can be observed across the two curves. The curve corresponding to ADSL peers drops lower than that of Ethernet peers, indicating a higher early departure rate in general among ADSL peers than that among Ethernet peers. The log-rank test results give \( p \approx 0 \), which further confirm the observed difference.

### 4.2.5 Effect of NAT

Real-world Internet users may be behind various NAT gateways for better networking security. The distribution of UUSee users across different connection types, with re-
spect to direct connection (not behind a gateway), indirect connection via a cone NAT, a symmetric NAT, or any other type of NAT’s (including host-restricted cone NAT, port-restricted cone NAT, etc.) is approximately 41% : 45% : 8% : 6%. We can see more than half of all peers from the traces are behind NAT gateways. A large portion of NAT devices apply some per-user limitations on the concurrent connection number and network throughput to guarantee fairness among all users behind the NAT. Such limitations may affect the streaming of peers behind the NAT in a negative fashion, which require a stable streaming rate at all times. Therefore, we wonder any possible negative effects of the gateways on the longevity of peers.

We first categorize peer sessions to two classes, direct connection and connection via an NAT, and plot the survival functions of the two session groups in Fig. 4.12. No significant difference between two curves are observed, and the result of log-rank tests, \( p \approx 0.216 > 0.05 \), also fails to reject the null hypothesis that the two curves are statistically equivalent.

![Figure 4.12: Survival curves for peer sessions that are directly connected and behind NATs.](image)

![Figure 4.13: Survival functions for peer sessions behind full cone NATs and other types of NATs.](image)

Among various types of NAT, the full cone NAT is NAT traversal friendly, while symmetric NAT, host-restricted cone NAT and port-restricted cone NAT are not. If connections from the outside world to a peer behind a NAT belonging to the latter
families are to be blocked, the peer loses the chances to be passively connected, resulting in its limited knowledge of possible stream suppliers. To investigate possible impact of different NAT types, we next categorize peer sessions behind NAT to two classes, behind cone NAT and behind other types of NAT, and plot the survival curves of the two session groups in Fig. 4.13. We observe that the two curves largely overlap with each other. The log-rank test $p \approx 0.152 > 0.05$ does not present any evidence for the existence of significant statistical difference as well.

### 4.3 Modeling Peer Longevity: The Cox Regression

With various important influential factors identified, we now seek to model the peer longevity as a function of these factors, based on the Cox regression model, introduced in Sec. 2.3.

In our regression modeling, the potential covariates are selected corresponding to the influential factors we have observed. The potential covariates, along with their description and type, are listed in Table 4.1. In order to use the Cox regression model to formulate the relationship among these covariates and the hazard rate, we first need to check if the proportional hazards assumption is satisfied, and may adjust the form of the covariates in Table 4.1 to be included in the Cox model, in order to meet the proportional requirement. Once the assumption check is passed, we proceed to derive the values of regression coefficients $\beta_k, k = 1, \ldots, p$ in the model. Using the Cox model, we can then estimate the probability that a session lasts to any specific time $t$ (i.e., the survival curve of the session), given the values of the covariates for the session and using the derived coefficients.
Table 4.1: Potential covariates in Cox Regression Model

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>BUFAVG</td>
<td>Average buffering level of the session</td>
<td>Continuous</td>
</tr>
<tr>
<td>BUFSTD</td>
<td>Standard deviation of buffering level during the session</td>
<td>Continuous</td>
</tr>
<tr>
<td>BUFINIT</td>
<td>Initial buffering level of the session</td>
<td>Continuous</td>
</tr>
<tr>
<td>INDAVG</td>
<td>Average incoming degree during the session</td>
<td>Continuous</td>
</tr>
<tr>
<td>INDSTD</td>
<td>Standard deviation of incoming degree during the session</td>
<td>Continuous</td>
</tr>
<tr>
<td>ADSL</td>
<td>The last-mile connection is ADSL or not (1: ADSL, 0: Ethernet)</td>
<td>Categorical</td>
</tr>
<tr>
<td>TOD</td>
<td>Joining time of the day (TOD ∈ {0, 1, ..., 23}, corresponding to the hours of the day)</td>
<td>Categorical</td>
</tr>
</tbody>
</table>

4.3.1 Proportional Hazards Assumption Checks

Categorical Factors

One approach to check the proportional hazards assumption for a categorical covariate, *i.e.*, whether or not the hazard ratio of sessions with different values of a categorical factor is a constant, is to group the sessions based on the values of the corresponding categorical factor, and plot the values of $-\log(\hat{S}(t))$ against $t$ for each session group [21], where $\hat{S}(t)$ is the estimated survival function of the group. The plots for the two categorical covariates in our model are shown in Fig. 4.14 and Fig. 4.15. If the hazard ratios do not change with time, the curves in the figure should be approximately parallel, *i.e.* there is an approximate constant vertical distance between each pair of them at all times. However, in Fig. 4.14, we observe that the curves intersect with each other, indicating the violation of the proportional assumption for TOD. In Fig. 4.15, the intersection at round 50 reveals that the covariate ADSL also violates the proportional assumption of Cox regression model.
Figure 4.14: Proportional hazards assumption check for the categorical factor TOD.

Figure 4.15: Proportional hazards assumption check for the categorical factor ADSL.
Given the non-proportionality of the categorical factor, we modify our model in (2.1) to the stratified Cox model [21], in order to accommodate the categorical factors. The stratified Cox model extends the basic Cox model by incorporating strata, where each stratum corresponds to one hazard rate function, that models the hazard rate of sessions corresponding to one specific value of each categorical factors. The stratified Cox model with \( n \) strata \((i = 1, \ldots, n)\) is given by:

\[
\lambda_i(t; z) = \lambda_{0,i}(t) \exp(\beta^T z), \quad i = 1, \ldots, n.
\] (4.1)

In our modeling, we have two categorical variables with 2 possible values and 24 possible values, respectively, and thus the total number of strata \( n \) is \( 2 \times 24 = 48 \). We note that in such a stratified Cox model, each stratum may have different baseline hazard functions, but all strata share the same coefficient vector \( \beta \) because all other non-stratified factors are required to have the constant influence to the hazard functions.

**Continuous Factors**

For a continuous covariate, the proportional hazards assumption implies that it should have a linear influence on the hazard ratio, i.e., the hazard ratio between a session with \( \text{BUFINIT} = 300 \) and one with \( \text{BUFINIT} = 340 \) should be the same as that between a session with \( \text{BUFINIT} = 400 \) and one with \( \text{BUFINIT} = 440 \). The approach to conduct such an assumption check is to plot the Poisson residual curve [21] for each continuous factor. The Poisson residual of a covariate reflects the impact of this specific factor in the hazard rate function: a positive Poisson residual implies a positive impact, i.e., the hazard rate is greater with a larger value of the covariate, while a negative Poisson residual indicates a negative impact, vice versa. The Poisson residual curve should be approximately linear if the hazard ratio between any two sessions with two specific values of the factor is a time-independent constant. We plot the Poisson residual
curves (black solid lines) for all our continuous factors in Fig. 4.16–4.21, along with their standard error confidence bands (black dashed lines), and the linear approximation lines (in red). The plots show that many of the Poisson residual curves are not satisfactorily linear, reflecting violation of the proportionality in certain value ranges of the factors. We thus seek to make necessary adjustments for the form of the covariates, such that all the new covariates have a linear influence on the hazard ratio.

![Figure 4.16: Proportional hazards assumption check for BUFAVG.](image1)

![Figure 4.17: Proportional hazards assumption check for BUFSTD.](image2)

Fig. 4.16 shows an approximated linear curve in the majority range of the average buffering level, except in the range of 460 to 500. To include BUFAVG into the Cox
model, we only keep its value range of \([0, 460]\), \(i.e.,\) we exclude sessions with \(\text{BUFAVG}\) in the range of \([460, 500]\) when we derive the model coefficients, which nevertheless only represent a small portion \((\approx 7\%)\) of all the sessions based on our measurement study.

The major part of the Poisson curve in Fig. 4.17 can be approximated by two linear segments. To include \(\text{BUFSTD}\) into our Cox model, we exclude sessions with \(\text{BUFSTD}\) in the range of \([0, 16]\) (which only represent a few extremely short sessions), and include a new variable \(\text{BUFSTD}_L\) to describe the section of \(\text{BUFSTD}\) with larger values, corresponding to the range of the second linear segment we approximate in Fig. 4.17:

\[
\text{BUFSTD}_L = \begin{cases} 
\text{BUFSTD} - 40 & \text{if } \text{BUFSTD} \geq 40 \\
0 & \text{otherwise}
\end{cases}
\]

Figure 4.18: Proportional hazards assumption check for \(\text{BUFMIN}\).

Similarly, the major part of the Poisson curve in Fig. 4.18 can be approximated by two linear segments. To include \(\text{BUFMIN}\) into our Cox model, we exclude sessions with \(\text{BUFMIN}\) in the range of \([460, 500]\) (which only include a few sessions), and include a new covariate \(\text{BUFMIN}_L\) to describe the section of \(\text{BUFMIN}\) corresponding to the linear segment in the range of \([359, 460]\):
Figure 4.19: Proportional hazards assumption check for BUFINIT.

The Poisson curve in Fig. 4.19 can be approximated by three line segments connected at two knots at 48 and 351, respectively. Since each section of BUFINIT includes a substantial number of sessions, we include two new covariates, BUFINIT_M and BUFINIT_L, to describe the sections of BUFINIT corresponding to linear segments in the middle and to the right, respectively:

\[
\text{BUFINIT}_L = \begin{cases} 
\text{BUFINIT} - 359 & \text{if } \text{BUFMIN} \geq 359 \\
0 & \text{otherwise;}
\end{cases}
\]

In Fig. 4.20, the Poisson curve of INDAVG can be nicely fitted by one line, revealing the proportionality of the factor on the hazard ratio. In Fig. 4.21, we remove the leftmost part (corresponding to INDSTD in the range of 0 – 7 with a few sessions), and fit the rest of the curve with a line.
Figure 4.20: Proportional hazards assumption check for INDAVG.

Figure 4.21: Proportional hazards assumption check for INDSTD.
After the adjustment, a covariate vector $z = (z_1, \ldots, z_p)$ with $p = 8$ components is used in our stratified Cox model. The covariates are summarized in Table 4.2. We note that in Fig. 4.16–4.21, all the linear approximation lines fall within the confidential bands of the original Poisson residual curves, indicating that the Poisson curves in those sections can be effectively approximated by the linear segments. Therefore, after the adjustment, all the covariates we now use in the Cox modeling satisfy the proportional hazards assumptions.

### 4.3.2 Estimation of the Coefficients

We next use a specific Cox regression technique proposed by Andersen and Gill [10], to estimate the stratified baseline functions $\lambda_{0,i}, i = 1, 2, \ldots, 48$ and the coefficient vector $\beta$ in our stratified Cox model in (4.1). The basic methodology is to reformulate the Cox model as a counting process, and apply a maximum likelihood estimation algorithm which utilizes the local martingale [10].

Table 4.2 gives the coefficients of the covariates along with their standard errors, estimated using information of 12866 session from 20 unpopular channels in our traces. The 20 channels, whose average concurrent population varies from 48 to 457, are randomly chosen from all 530 unpopular channels contained in our traces. The purpose for such sampling is not only to expedite the speed of the regression process, but also to exhibit the usefulness of our model, trained using only a limited set of samples, as is to be illustrated in the following subsection. We have also computed the $p$ values to test the significance of all the coefficients, which are all far below 0.05, suggesting the significance of the covariates.

The signs of $\beta$ for different covariates are consistent to our previous observations in Sec. 4.2. For example, the negative $\beta$ value for BUFAVG validates our earlier observation on its positive influence on peer longevity. With respect to the factor of initial buffering level, its influence in the value range of $\text{BUFINIT} \geq 351$ can be reflected
by $\beta_{\text{BUFINIT}} + \beta_{\text{BUFINIT}_M} + \beta_{\text{BUFINIT}_L} = 0.011 - 0.012 - 0.0029 = -0.0039 < 0$, which confirms that a good initial playback experience encourages users to stay longer in the channel. We have also computed the $p$ values to test the significance of all the coefficients, which are all far below 0.05, suggesting the significance of the covariates.

Table 4.2: Covariates and Coefficients for the Cox Model in (4.1)

<table>
<thead>
<tr>
<th>Covariate</th>
<th>$\beta$</th>
<th>Std. Err.</th>
<th>Covariate</th>
<th>$\beta$</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>BUFAVG</td>
<td>-0.0074</td>
<td>1.7e-3</td>
<td>BUFINIT</td>
<td>0.011</td>
<td>1.8e-3</td>
</tr>
<tr>
<td>BUFSTD</td>
<td>0.059</td>
<td>2.9e-3</td>
<td>BUFINIT_M</td>
<td>-0.012</td>
<td>1.9e-3</td>
</tr>
<tr>
<td>BUFSTD_L</td>
<td>-0.044</td>
<td>2.9e-3</td>
<td>BUFINIT_L</td>
<td>-0.0029</td>
<td>4.9e-4</td>
</tr>
<tr>
<td>INDAVG</td>
<td>-0.051</td>
<td>1.9e-3</td>
<td>INDSTD</td>
<td>0.046</td>
<td>2.1e-3</td>
</tr>
</tbody>
</table>

4.3.3 Model Validation

With the Cox regression model established, we can now derive the survival curve of a session with covariate vector $z$ in a certain category of ADSL and TOD. The estimator of the survival function with covariate vector $z$ at time $t$ is given by

$$S_i(t; z) = \exp \left( - \int_0^t \lambda_i(u; z) du \right),$$

where $\lambda_i(u; z)$ is the stratum corresponding to a specific category of ADSL and TOD of sessions. We may use the expected session time of the survival curve corresponding to a session with $z$, as the most probable duration of the session. In this way, given a covariate vector $z$ and the corresponding ADSL and TOD, we are able to predict the most probable duration of a session using our stratified Cox model. Recall that our regression model is trained using only a limited set of session data from 20 randomly selected unpopular channels. We now evaluate its accuracy in estimating the duration of sessions in other channels.
Figure 4.22: Regression model validation by prediction of the peer longevity.
We calculate the overall influence of the continuous covariates by $\beta^T z$, referred to as the *global impact* to the hazard rate. We group all the sessions in the unpopular channels in UUSee (other than the 20 channels we used in the regression), by their global impact and values of ADSL and TOD, and plot the median session duration for session groups at different levels of their global impact in different cases of ADSL and TOD, as shown by the bar plotting in Fig. 4.22. In solid curves, we also plot the session duration predicted using our Cox model in (4.1) at each global impact level, and the 75% confidence intervals (in dashed lines). The actual median session durations in all four figures fall into the 75% confidence intervals of the prediction, which validates the usefulness of our regression model — derived using a small portion of session data — in accurately capturing the session duration patterns for all the unpopular channels.

### 4.4 Model Implications to Unpopular Streaming Channels

The influential factors and peer longevity model we derived in the previous sections provide us useful insights towards the cause to peer instability in unpopular channels, and guide us towards possible improvement of peer stability, for the ultimate goal of enhancing streaming quality in those channels.

#### 4.4.1 Impact of the Streaming Quality Factors

Three streaming quality factors are involved in our Cox regression model. We seek to investigate the relative significance of their impact on peer longevity, by calculating an impact value, $\beta_k z_k - \min_y (\beta_k y_k)$, for each individual session with a specific $z_k$, with respect to the three streaming quality factors of average buffering level, standard deviation of buffering level and initial buffering level, respectively. Here, $\min_y (\beta_k y_k)$ is
the minimal impact value for the corresponding streaming quality factor over all the sessions. We then compute the ratio of the impact values of the three streaming quality factors for each session, and derive the average ratio across all sessions. The normalized average ratio in the percentage format is $16% : 33% : 51\%$, which exhibits the relative level of user’s intolerance to the three streaming quality factors, respectively.

**Importance of the Initial Buffering Level**

An intriguing discovery is that the initial buffering level is the most important streaming quality factor affecting peer longevity. Using the coefficients in Table 4.2, we derive the coefficient $\beta$ corresponding to the initial buffering level factor in the range of 48 to 351 is $\beta_{\text{BUFINIT}} + \beta_{\text{BUFINIT,M}} = -0.001$, and the coefficient corresponding to the range of 351 and 500 is $\beta_{\text{BUFINIT}} + \beta_{\text{BUFINIT,M}} + \beta_{\text{BUFINIT,L}} = -0.0039$. The more negative coefficient in the latter case illustrates that when the initial buffer is relatively full, a small increase of buffering level induces more significant decrease of failure probability, i.e., more evident effect in keeping peers longer in the system. Therefore, to promote the stability of high-contribution peers, efforts should be made to guarantee them a high initial buffering level.

Consistent to our previous observation in Sec. 4.2, for $\text{BUFINIT}$ less than 48, $\beta_{\text{BUFINIT}}$ shown in Table 4.2, is greater than zero, which implies that most of peers are tend to leave the channel if the initial playback experience is unsatisfactory. Meanwhile, when initial buffering level is between the range from 48 to 351, the overall coefficient for initial buffering level is calculated as $\beta_{\text{BUFINIT}} + \beta_{\text{BUFINIT,MED}} = -0.001 < 0$, indicating that users begin interested in staying in the channel if the initial buffering level is high. However, such beneficial impact over peer longevity is relative weak, as the overall coefficient is smaller than that for the range of initial buffering level between 351 and 500, given by $\beta_{\text{BUFINIT}} + \beta_{\text{BUFINIT,MED}} + \beta_{\text{BUFINIT,HI}} = -0.0039$. Hence, a stronger beneficial impact is observed when the initial buffering level is over a high level (over 351).
We can conclude that users who experience good initial streaming, thus satisfactory initial playback experience, are very likely to stay longer in the P2P system.

### Average Buffering Level vs Standard Deviation of the Buffering Level

The ratio between the impact values of the average and the standard deviation of the buffering level, 16% : 33%, shows that users are twice sensitive to the unfavorable fluctuation of the streaming quality, as compared to the average level of the streaming quality. Therefore, it is more important to provide user a smooth streaming quality, *i.e.*, by guaranteeing a consistent streaming bandwidth, in order to encourage peers stay longer in a channel.

### Minimal Buffering Level

The positive values for minimal buffering level imply that a bad experience, in term of streaming quality, is unavoidable during a user session and tolerable for users. If a peer has already in a channel, such sudden drop of streaming quality will not affect peer longevity too much.

#### 4.4.2 Impact of the Incoming Degree Factors

Following a similar methodology, we further compare the impact of the average peer indegree and the standard deviation of peer indegree, and derive a user’s intolerance ratio of 38% : 62% to the two factors. It confirms that in small channels, peers are much less tolerant to neighbor churns than the average level of neighbor numbers. Therefore, the P2P protocol should always try to find stable good neighbors for each peer, the number of which may be small, but is much desirable than a large number of transient neighbors.


4.4.3 Impact of Internet Access Types

Although in our stratified Cox regression model, we cannot get the numerical coefficient $\beta$ for non-proportional categorical factor ADSL. We still can identify the difference, in terms of effects to session duration, between Ethernet and ADSL, by comparing the estimated survival curves of two types of last-mile Internet service. As we have observed in Sec. 4.2, the curve for $ADSL = 1$ is below that of $ADSL = 0$. We also further comparing the baseline hazard functions for strata with different ADSL. The numerical comparisons also confirm our claim that users served by Ethernet are more likely to have longer session duration. Such observation implies, on one side, we may need to make better effects to persuade ADSL users stay in the channel, such providing them high-quality and stable neighbors to sustain a delightful user experience; on the other side, we may prioritize Ethernet users because they are more probable to stay in the system, and thus assist other existing peers and newcomers.

4.4.4 Impact of the Peer Joining Time

We further investigate the underlaying implications for the non-proportional categorical factor TOD. Similar to the categorical factor ADSL, we compare the effect for different levels of TOD by comparing their corresponding baseline functions $\lambda_{0,i}$. We observe that in small unpopular channels, during evening leisure hours from 7 p.m. to 11 p.m., the probability of early departures is 23% lower than that during normal hours, i.e. the peer churn is much less significant in evening hours.

4.4.5 Satisfactory Index

Based on the Cox model, we design a satisfactory index to evaluate peer longevity using the influential factors:

$$SI = \beta^T z = \sum_{k=1}^{p} \beta_k z_k.$$
CHAPTER 4. DECRYPTING PEER INSTABILITY IN UNPOPULAR CHANNELS

Indeed this is a linear combination of influential covariates weighted their corresponding coefficients $\beta$. As we have shown during model validation in Sec. 4.3.3, this index can objectively reflects the overall influence to the expected peer longevity. The smaller satisfactory index is, the low probability of early departure happens, thus the longer expected session duration is.

Even without the knowledge of underlying baseline functions $\lambda_0$, we are still able to compare any two specific sessions, by comparing their satisfactory index with corresponding covariate vectors. With the help of satisfactory index, we can easily extend existing peer selection algorithm or block scheduling algorithm, in order to improve the overall system performance.

4.4.6 Discovering Stable Peers

Similar to the superior index proposed in the previous chapter, the Cox model we derived from traces of unpopular channels can be used to estimate and compare the stability of peers in unpopular channels and thus help in selecting stable neighbors for the peers. For peers in the same categories of last-mile connection type and joining time, the failure probability can be evaluated by $\beta^T z = \sum_{k=1}^{p} \beta_k z_k$ using the continuous factors. Here the average/standard deviation of a factor can be computed using values in the past history of a peer session. For peers with different connection types and joining times, our earlier observations can be utilized to compare the relative stability of peers, e.g., we have observed that Ethernet peers tend to have a longer life time and peers joining in daily rush hours (7 p.m. to 11 p.m.) are more volatile, etc. Note that in most cases we do not need to know the accurate lifetime of a peer, but only the relative stability among a number of candidate peers. Our Cox model provides us useful insights for such peer longevity comparison, and can assist in peer selection or block scheduling algorithms to promote the overall stability in small channels towards better streaming quality.
4.5 Summary

In this chapter, we put our focus on a large number of unpopular channels in real-world P2P live streaming systems. Taking the full advantage of over 130 GB worth of traces from UUSee, we explore the important factors that influence peer longevity. We have discovered that the initial buffering level, incoming degree, peer joining time and connection type are key factors that decide the duration of peer sessions. Furthermore, we model their relationship into a Cox regression model, and then discuss implications of our model and derive a number of useful insights to promote peer stability.
Chapter 5

Concluding Remarks and Future Work

In this thesis, taking full advantage of over 130 GB worth of real-world traces from a commercial P2P streaming system — UUSee, one of the leading P2P multimedia solution providers in mainland China — we aim to measure the peer lifetime pattern in production peer-assisted live streaming systems, and discover useful insights to prompt the overall system performance. Different from existing literatures, which simply characterize the peer lifetime distribution and some correlations, we conduct in-depth measurements on peer longevity, using survival analysis techniques. In this thesis, we have not only identified critical influential factors to peer longevity, but also have modeled their relationship into the Cox regression model to discover valuable implications.

The first part of this thesis focuses on popular channels in real-world P2P streaming systems, especially extreme cases of flash crowds. Once the server’s sustainable threshold is reached and then breached, we have to prefer superior peers, who have better longevity and larger upload contribution. In the part of this thesis, we first identify key influential factors that decide the duration of peer sessions, and then model their relationship into the Cox regression model. Similarly, for the bandwidth contribution ratio at each peer, we discover the impact of peer initial buffering level and
ISP membership, and model their linear correlations. To demonstrate the application of our discoveries, we propose the superiority index to distill superior peers, and apply this index in a natural selection algorithm to improve the session duration of high contribution peers. Based on a replay of real-world streaming traces, our simulation validates the effectiveness of this superiority index in improving the overall stability and scalability of the P2P streaming system.

In the second part of this thesis, we switch our focus from popular channels to unpopular channels, as unpopular channels usually represent the majority of available channels in real-world streaming systems. From trace studies, we have shown that users in such unpopular channels experience lower streaming quality, compared to popular channels, and such unsatisfactory streaming quality is closely related to the shorter peer lifespan in unpopular channels. To improve the streaming quality in these unpopular channels, we thoroughly characterize important factors that influence peer longevity, including the initial buffering level, incoming degree, Internet access type, and peer joining time. Furthermore, we fit these factors into the Cox regression model to model correlations between influential factors and peer longevity. Based on our model, we discuss several implications and derive a number of useful insights to promote peer stability in unpopular channels.

Equipped with survival analysis techniques, we have applied in the lifespan measurement on P2P live streaming applications, we may further study the longevity pattern in peer-assisted on-demand streaming systems, which are more complicated and challenging than live streaming. In the on-demand scenario, as peers are allowed to exchange media blocks with other peers, who are not watching the same movie but have it stored in their caches, it becomes even more critical to have as many as peers online to share videos they cached, i.e., we wish to promote peer longevity in on-demand systems. However, it must be noted that the multi-channel sharing and frequent VCR-like operations in on-demand streaming systems greatly increase the
complexity of applying survival analysis. These challenges imply possible directions for the future research.
Bibliography


[12] W. S. Cleveland. Lowess: A Program for Smoothing Scatterplots by Robust Lo-


    1976.


    Maximum Likelihood Variance Component Estimation. Technometrics, 18(1):11–
    17, 1976.

[18] E. L. Kaplan and P. Meier. Nonparametric Estimation from Incomplete Observa-

    2007.

[20] B. Li, S. Xie, Y. Qu, G. Keung, C. Lin, J. Liu, and X. Zhang. Inside the New Cool-


