On the Potential of Automated Downloads for MOOC Content on Mobile Devices

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***Abstract*—Mobile applications for MOOC platforms often can download learning material — namely videos — for later usage without the need for an Internet connection. As learners want to perform such data-intensive tasks with a WiFi connection, manual planning is required. By automating the download management, learners can be supported by always having video material available independent of the current Internet connection. This work examines the current download behavior shown in three MOOC courses. Hereby, influencing factors like the dependence on time and date, as well as the network state were analyzed. The results show that learners are already aware of data-intensive learning activities. They mostly download videos when connected to a WiFi network and consume pre-downloaded video content when using a cellular connection. An estimate of the potential for automated downloads using a simplified approach revealed the possibility of making an additional 19% of the video consumption network independent. The download behavior in the three courses examined differed noticeably so that automated downloads should be seen as an additional feature that can be activated per course.**

***Index Terms*—MOOCs, Mobile Seamless Learning, Mobile Learning, E-Learning**

I. Introduction

With the increasing ubiquitous availability of mobile devices, learners in Massive Open Online Courses (MOOCs) were able to choose their preferred learning device and learning method in addition to regular desktop use [1], [2]. Unlike desktop computers, mobile devices are not tied to a stationary learning environment as they can independently connect to the Internet [3]. At the same time, mobile networking creates a new dependency on a potentially unreliable network connection and can generate additional data transfer costs [4]. To overcome this dependence, MOOC platform providers added functionalities for mobile applications to download learning material for later usage without the need for an Internet connection [5]. While these user-initiated downloads enhance the overall learning experience by making the learning process independent of the available network connection [6], they also mean an additional effort for learners who need to plan their future learning sessions [7], [8]. Because new learning material in MOOCs is often released weekly [9], downloading all content at once is not applicable.

Extensive research on download behavior has not yet been conducted. Therefore, this paper examines different aspects of the use of download functionalities to create a better understanding of learners' actions and needs. Downloading learning material — especially video content — is a data-intensive task. Depending on the learners' access to reliable Internet connections [10], mobile data plans, and the provided cellular infrastructure in general [11], learners can tend to prefer a WiFi connection in a frequently visited location over a cellular connection. In this way, there will be no additional costs as such Internet connections are commonly priced in a flat-rate model. Also, in times of intensive remote working, network activity and the load on servers increase [12]. By downloading learning material once (and during periods of low network load), rather than streaming video content each time, the overall network load can be reduced. Furthermore, storage capacities of the mobile device can also be a decisive factor for download behavior, as learners cannot exceed these limitations. Learners might only be able to download a certain amount of learning material at once. Considering this, modern MOOC platforms provide their content in different resolutions to let learners decide between optimizing for quality or storage capacity.

By analyzing the current download behavior of MOOC participants on mobile devices, a better understanding of automated download functionalities is created. This will consequently support MOOC platform providers in building adequate features that reduce the needs for resource planning, leading to a more seamless learning experience for mobile learners [13], [14]. Similar features have already applied in the context of streaming services [15]. To explore the current download behavior and thus the potential for automated downloads for MOOC content, the following research questions were formulated:

- RQ1 What characteristics are suitable for describing the download behavior on a MOOC platform?
- RQ2 To which extend might automated downloads support learners?

II. Current Download Behavior Characteristics

In this section, the download behavior is examined, which is currently shown by learners with mobile devices when having no automated download functionality for MOOC content available. For this, several aspects have been considered. The feasibility and usefulness for each aspect are evaluated individually, though some aspects are interconnected.

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A. Methodology

The mobile applications for the HPI MOOC platform are being developed independently for iOS and Android with the respective native SDKs. Nonetheless, feature parity across mobile applications is always strived for. In both applications, learners can download video streams for later usage. While the Android application can download streams in standard definition (SD) or high definition (HD), the iOS application utilizes integrated system functionality and HTTP Live Streaming (HLS) for downloading video streams[1]. By doing so, the iOS application offers the learners more fine-grained settings for the quality — and thereby used storage space — of downloaded video streams. Both applications create analytics events when learners are starting the download of a video stream. Besides the identifier of the video, every event includes the current timestamp and the available storage on the mobile device. When the learner starts the playback of a video stream, an analytics event is created which includes — among other data — the video identifier and the network type the device is connected with. For this study, three courses are examined that ran on openHPI — an instance of the HPI MOOC platform, which offers courses about digital technologies and other CS-related topics. All courses ran over several weeks from January 2020 to April 2020 and followed the traditional MOOC structure — self-tests and interactive exercises between videos. Although all courses remained available after the course end, this study only examines the learner behavior during the course period.

TABLE I: Information About Studied Courses

Course	Material		Active Learners (Shows)		
	Items	Videos	N	Mobile*	Download†
data-engineering2020	290	144	10823	0.25	0.10
javaeinstieg2020	194	49	10441	0.15	0.03
neuralnets2020	133	62	6865	0.19	0.05

*Quota of users who used the mobile applications
†Quota of users who used the mobile applications and downloaded content

Table I contains descriptive metrics about the studied courses, as well as about the learner community. As two courses — *data-engineering2020* and *neuralnets2020* — primarily used videos to transfer information, approximately half of the provided learning material was video content. The course *javaeinstieg2020*, on the other hand, made extensive use of interactive programming exercises. Therefore, the learning material provided in this course only consists of videos for approximately 25%. The usage of these interactive exercises in this course can also help to justify the lower quota of learners who made use of the mobile applications (0.15) as the exercise tool — although accessible and functional — is not optimized for being used on mobile devices. In the two other courses, a higher number of learners used the mobile applications to access to learning material (0.19–0.25).

[1] HLS streams bundle multiple streams with different resolutions. Depending on the current network throughput, the video stream with the highest resolution is selected, which allows a continuous playback without additional buffering.

B. Download State During Video Consumption

Whereas the mobile applications of the HPI MOOC Platform are fully functional both with a WiFi connection and with a cellular connection, learners might show different behavior concerning downloading content and consuming content when using either data connection. Learners having access to an unreliable or slow Internet connection might still prefer downloading learning material beforehand even though they are connected to a WiFi network when consuming the content. 93% of all video downloads were started when the mobile device was connected to a WiFi network, with only 7% of downloads started over a mobile connection. This aligns with the motivation of this work that learners are aware of the network load and the effects like additional costs and a potentially unreliable network connection.

TABLE II: Network State During Video Consumption

Course	Started Video Playbacks		Data Source	
	Network State	N	Online	Offline
data-engineering2020	WiFi	35986	0.73	0.27
data-engineering2020	Cellular	15932	0.34	0.66
javaeinstieg2020	WiFi	986	0.84	0.16
javaeinstieg2020	Cellular	372	0.73	0.27
neuralnets2020	WiFi	485	0.79	0.21
neuralnets2020	Cellular	441	0.50	0.50
Total	WiFi	37357	0.74	0.26
Total	Cellular	16745	0.36	0.64
Total	Combined	54202	0.62	0.38

Table II displays the ratio between the current network connection type and the data source for video playbacks. When connected to a WiFi network, the majority of video playbacks (0.73–0.84) used the online data source, meaning the data was streamed to the mobile device. However, when using a cellular connection, the learners behaved differently in the studied courses. While the *javaeinstieg2020* course showed a similar distribution (*online* as data source: 0.73), only half of the participants of the *neuralnets2020* course referred to the offline data source for video playback with a cellular connection. In the *data-engineering2020*, the majority of learners (0.66) used the offline data source when connected to a cellular network. Across all three studied courses and all network connection types, 38% of the video playbacks on the mobile devices were started referring to the offline data source.

The authors believe that the analysis of the *data-engineering2020* course yields the results which best describe the download behavior for traditional MOOCs without interactive exercises. This is based on the number of active learners and the number of started video playbacks in the course. As shown with the *javaeinstieg2020* course, these results may vary greatly if courses use interactive exercises.

C. Dependence on Date and Time

As planning and preparing learning sessions is a manual task, some time effort is required by the learner when downloading multiple learning material items. Depending on the learners' routines, these download sessions might occur in a designated time slot (e.g., in the morning or the evening) or when new course material is made available. Therefore, it can be insightful to have a closer look at the calendric and time-dependent aspects of the current download behavior.

In Figure 1, heatmap charts are shown for each of the studied courses. In each chart, the number of started downloads is visualized per weekday and hour of the day. In each of the three courses, most downloads were triggered on Wednesdays. This caused by the fact that all courses chose this weekday to published new learning material. During this day, there was an increased number of downloads started in the morning (directly after new content was available) and in the evening. This effect is best observed with the courses *data-engineering2020* (see Figure 1(a)) and *javaeinstieg2020* (see Figure 1(b)) but can be influenced by the different learning routines and preferences of the learners. Other courses on openHPI, which publish new learning material on a different day of the week, report similar behavior on these days.

While for the courses *data-engineering2020* and *neuralnets2020* the download activity is almost exclusively performed on the day new material was made available, learners in the *javaeinstieg2020* course acted a bit looser in that they triggered downloads scattered over the week (see Figure 1(b)). Complementary, Figure 2 includes plots of the number of started downloads over the course period. For each course, the days with high download activities are visible and spaced every seven days (the length of a course section). Thereby, it is proven that the results displayed in Figure 1 are not skewed by a one-time high of download activities. It can be noted that with two courses, the number of downloads decreases over the course duration. However, this is likely to be influenced by the decreasing number of learners as some learners stop participating during the course period.

D. Quality of HLS Downloads and Course Download Sizes

Each HLS video stream is usually available in different resolutions which are measured in bits per second. Those bitrates vary depending on the compression rate and pixel information of the video content. When downloading an HLS stream, only one of the available resolutions can be selected for download. As bitrates are not uniform across all videos, four resolution levels have been defined independently of the actual bitrates of the HLS video streams — *low*, *medium*, *high*, and *best*. Each resolution level has an assigned minimal bitrate. When starting a download of an HLS video stream, the system picks the lowest available bitrate which is higher than the requested minimum bitrate for the preferred resolution level. If none of the available bitrates is greater than the preferred minimum bitrate, the highest bitrate is selected for download. Via a separate menu in the mobile application, learners can set their preferred video download resolution. By default, the lowest bitrate option is selected to minimize unintentional storage usage.

TABLE III: Distribution of Used Video Qualities

	Downloads	Video Quality			
Course	N	low	medium	high	best
min. bitrate (in bit/s)		$2 * 10^5$	$4 * 10^5$	$5 * 10^6$	$1 * 10^7$
data-engineering2020	29655	0.74	0.08	0.09	0.09
javaeinstieg2020	1461	0.70	0.14	0.03	0.13
neuralnets2020	2668	0.61	0.06	0.20	0.13
Total	33784	0.74	0.08	0.09	0.09

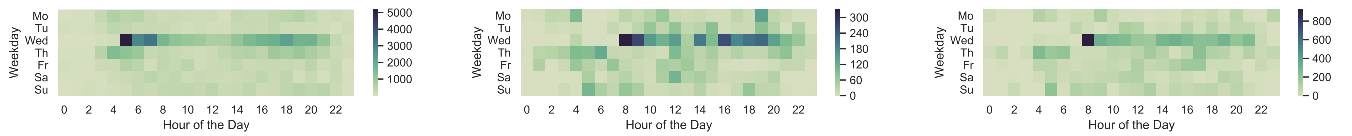
Table IV shows the defined resolution levels and the respective minimum bitrates, as well as the quota of downloads which were started with the respective resolution level in each course. The most often selected option used for downloading videos is the lowest minimum bitrate (0.61-0.74). The reason for this preference can be twofold. Either learners wish for downloaded material to take up the smallest amount of storage space as possible or they never changed the respective preference. Downloads with the other available resolutions have on average approximately the same distribution across all studied courses — with smaller peaks within a single course. Learners of the *javaeinstieg2020* course also preferred the medium (0.14) and the best (0.13) resolution, while participants of the *neuralnets2020* course often chose to download video with the high (0.20) or best (0.13) minimum bitrate.

TABLE IV: Average Download Sizes per Section

	Videos		Download Sizes (in GB)			
Course	N	Duration	low	medium	high	best
data-engineering2020	24.00	136 min	0.32	0.54	1.50	1.50*
javaeinstieg2020	12.25	79 min	0.19	0.36	0.44	0.44*
neuralnets2020	15.50	205 min	0.43	0.90	1.57	1.57*

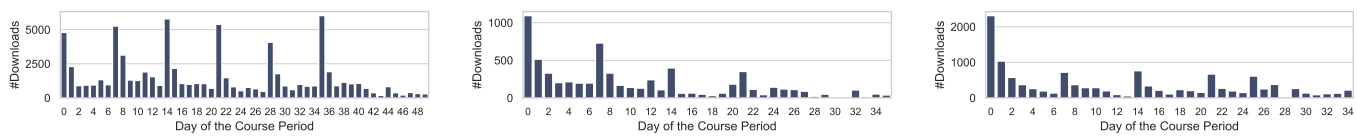
*Option 'high' provides already the maximal video quality

Depending on the selected video quality, the download size of a video varies. To provide an overview of the required storage capacities, Table IV list the required average download sizes for all videos in a section of each course, alongside with the average number of videos per section and their accumulated duration. To calculate the download size of an HLS stream, the duration of the video was multiplied by the matching bitrate — the smallest bitrate greater than the minimal bitrate of the respective video quality. Interestingly, the number of videos is not a reliable indicator of the overall download size. The courses *data-engineering2020* and *neuralnets2020* have approximately the same total video duration while differing greatly in the number of videos. Further, the video content of the video, the utilized compression algorithm, and the maximal video quality influence the download size. All courses show different download sizes which are neither proportional to the number of videos or their accumulated duration.



(a) data-engineering2020 (b) javaeinstieg202 (c) neuralnets2020

Fig. 1: Number of Downloads per Hour of Weekday



(a) data-engineering2020 (b) javaeinstieg202 (c) neuralnets2020

Fig. 2: Number of Downloads Over Course Period

E. Available Storage Capacities

Since the storage capacities of mobile devices — especially for devices running iOS — may not be expandable by users, the available storage capacity can be of great value to the user. Like any other storage-intensive app, the mobile apps for MOOC platforms may have to compete with other applications installed on the mobile device over the available storage. When downloading video material, a relevant amount of storage space can be used on the mobile device, as described in Subsection II-D. Therefore, the remaining storage capacities were examined for the learner who downloaded video material via the iOS application in the three studied courses. 46% of the learners had less than 3 GB of storage available. 16% had more than 3 GB, less than 6 GB available and 38% of the course participants had more than 6 GB of free storage on the mobile device. Some learners had up to 50 GB of unused storage space available on their mobile devices. Given the fact that new content becomes available over the course period, most of the learners' devices hold enough free storage capacities for downloading at least some of the provided video material. These results could have an impact on download behavior in self-paced courses, where learners could download several items at once. However, this is considered out-of-scope for this work.

F. Download Sessions

As the weekly published course material most commonly consists of multiple learning items, learners might tend to bulk-download all the new material in one sitting rather than downloading the new item after completing the previous one. For this, the concept of *download sessions* was defined to get a better understanding of this aspect of the learners' download behavior. All video downloads initiated by a learner within 30 minutes are considered to have been performed in a single download session by the learner.

The number of downloads sessions, as well as the average number of downloaded videos per session, are listed in Table V for each course and aggregated for all studied courses.

TABLE V: Download Sessions

	Downloads Session		Downloads per Session	
Course	N	N (norm.*)	Mean	Std.Dev.
data-engineering2020	4548	4.18	16.63	16.84
javaeinstieg2020	477	1.73	7.43	7.06
neuralnets2020	575	2.18	11.31	10.68
Total	5600	3.44	15.30	15.96

*Normalized by the number of active mobile learners (see Table I)

Learners in the course *data-engineering2020* performed the most download sessions per mobile learner (4.18) and downloaded most videos per download session (16.63). While the course *neuralnets2020* could report a slightly lower number of downloads per session (11.31) with fewer download sessions per mobile learner (2.18), the *javaeinstieg2020* course with interactive programming exercises shown the lowest number of download sessions per learner (1.73). On average, a learner will have about three download sessions during the course. However, it has to be considered that these results are influenced by learners dropping out of the course.

These download sessions represent the previously mentioned manual effort that learners have to undertake when preparing for upcoming network-independent learning activities. A perfect system for automated downloads would render these manual download sessions as obsolete. But with such a goal, the results from single courses could not be generalized for the whole learning community and, thus, would require customization and extensive amounts for collected usage data for each learner. By these means, the perfect system for automated download is not feasible and manual download sessions will continue to be relevant.

III. Estimating Support of Automated Downloads

After examining the download behavior and patterns currently show by the learners on the HPI MOOC Platform, the potential of automated downloads is estimated in this section.

By considering the previous findings and the current functionality of the mobile application, the estimation approach is shaped by the following assumptions. All assumptions have been simplified for this first study.

1) Learners prefer downloaded content over streamed content on mobile devices.
2) Learners always have access to WiFi networks at night.
3) Learners have sufficient storage capacities left on their devices.
4) Learners consume approximately three videos per day.
5) Videos are only consumed once by a learner.
6) All videos are consumed via a single mobile application.

Given these assumptions, a hypothetical automated download system would download the upcoming three videos, that have not been watched before, for each learner during the night when the mobile device is connected to a WiFi network. During the day, these three videos can be consumed independent of an Internet connection, whereas additional videos would generate network traffic. The next night, the download system would again be preloading upcoming videos while considering the videos that are still stored on the mobile device and have not been consumed by the learner.

A. Analysis

The effects of such a hypothetical automated download system were examined for the same three courses. For this, the date of the first video consumption on a mobile device was tracked for each video and learner. The first three video renditions were considered to be available offline, while the others were considered streamed. The results of the analysis are shown in Table VI including the quota of days on which all consumed videos have already been downloaded or would have been downloaded. The two courses *javaeinstieg2020* and *neuralnets2020* show a relatively high support rate (0.75–0.80) while in the *data-engineering2020* course only a support rate of 0.40 could be achieved. A possible influencing factor for that might be the number of videos that are made available in a course section (see Table IV). Additionally, the number of videos watched after exceeding the threshold of three videos per day was examined. Approximately six videos (exceeding by three videos) were watched per day in the course *javaeinstieg2020* and *neuralnets2020*, whereas approximately nine videos (exceeding by six videos) were consumed on active days in the *data-engineering2020* course. This again might be a result of the higher number of videos made available at once for a course week. In the three courses studied, on 19% of the days with learning activities, all video activities would have been additionally network-independent if a download system with a simplified approach had been used. However, about up to six video plays would have caused network traffic on average per day and learner.

B. Limitations

The already positive results of using such a simplified automated download system are likely to be influenced by the strict assumptions about the learner's download behavior.

TABLE VI: Simplified Approach for Automated Downloads

	Active Days*			Videos Exceeding Limit		
Course	N	Q_C	Q_P	N	Mean	Std.Dev.
data-engineering2020	16600	0.32	0.40	61554	6.17	6.27
javaeinstieg2020	2392	0.13	0.80	1457	3.07	4.28
neuralnets2020	2739	0.15	0.75	2778	3.99	4.69
Total	21731	0.30	0.49	65789	5.90	6.17

*Accumulated number of days on which learners consumed videos
Q_C: Quota of currently downloaded videos
Q_P: Quota of potentially pre-downloaded videos

While assumptions 1–3 are fundamental for download activities and can be universally deployed, the remaining assumptions are open for discussion and modification. Considering only three videos per day (assumption 4) was a good starting point for a first analysis. However, the number of video items consumed per day is dependent on factors that are for one individual for each learner and influenced by the day in the course period (e.g., the beginning of a new course week). As videos vary in duration, it appears reasonable to preload content until a certain accumulated content length is reached, rather than considering a fixed number of videos. The simplified download approach also only considers new unwatched content (assumption 5), which can be not available (e.g., when the learner reaches the end of a course week). Furthermore, learners tend to rewatch previous content for clarification and recap purposes. Keeping older video items stored on the device to reduced network traffic should also be considered when designing an automated download system. As the majority uses mobile applications in conjunction with the web application of openHPI (see Table I), videos will not only be consumed on a single mobile device (assumption 6). Therefore, the additional support rate of 19% needs to be placed into context with real-life learning activities.

IV. Discussion and Future Work

Based on the results of the analyses in the previous section, it becomes apparent that learners already aware and act consciously when handling data-intensive MOOC content on mobile devices. Reducing avoidable network traffic is of importance to learners, as well as having MOOC content available on their mobile devices all the time. As a result, most video downloads are performed when connected to a WiFi network, while the majority of videos consumed with a cellular connection have been downloaded beforehand (see Subsection II-B).

In the three studied courses, learners heavily downloaded newly available course material on the day of its publication (see Subsection II-C). This shows a high level of self-regulation among motivated learners than they starting consuming the content right away. As publication dates of new course content are known beforehand, they can be utilized by the download system. As shown in Subsection II-F, learners tend to download multiple videos in a single session instead of download items one after another. By design, downloading multiple items in bulk is an underlying principle of a system for automated download management. The estimation of the potential for automated downloads through pre-downloading the next three upcoming videos showed promising results by additionally covering 19% of the consumed videos. Nevertheless, depending on the concepts used in the MOOC (traditional, programming-oriented, etc.), learners can show different download behaviors. Thus, there is still room for improvement by considering course-specific factors and individual learner preferences. Further analyses of the required storage capacities when downloading videos and whole courses, as well as of the available storage capacities and the selected video quality revealed no storage restriction for automated downloads on mobile devices (see Subsection II-E).

However, a system for automated downloads to mobile devices should always be considered as an additional feature that the learner must knowingly activate. This prevents redundant network activities and unwanted storage usage. To further limit background activity, the download management system could be activated for individual courses only, instead of being applied for the entire mobile application. Through this work, the foundation for an automated download management system was defined. Further studies on a larger dataset should focus on the acceptance shown by learners, the changes in network load, and the implementation challenges specific to the context of MOOCs, as well as evaluating the download behavior in less technical courses. Also, follow-up analyses could investigate the effects of cancellation of downloads (by learners or by the system) and include other learning materials such as presentation slides.

V. Conclusion

This work examined the download behavior of MOOC content currently shown by learners with mobile devices based on collected events. For this, the download activities in three courses from the HPI MOOC Platform were recorded and analyzed. The results show that learners are already aware of the network state when performing data-intensive activities. They mostly download videos when connected to a WiFi network and consume pre-downloaded video content when learning with a cellular Internet connection. Hereby, the following characteristics have been identified to be useful when describing the download behavior shown by the learners (RQ1): Dependence of time and date, network state of the mobile device, and the number of downloads started in a single download session. In contrast, the download size of a course section, the video quality selected for download, and the available storage space on the mobile device were not decisive for the download behavior of learners.

To estimate the possible support of an automated download system, the theoretical effects of a simplified approach have been examined for the same three courses. Given that the first three new videos watched by a learner on each day would have been downloaded beforehand, 19% of the video consumptions would have been additionally network-independent (RQ2). Further, learners also watched approximately up to six additional videos and thus creating a starting point for further optimizations of automated downloads. With the addition of a well-designed system for automated downloads, learning experience on mobile devices will become more seamless as learners no longer have to prepare for network-independent learning sessions.

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