Human Computation in Online Video Storytelling

Philo D. I. van Kemenade

Submitted in partial fulfillment of the requirement of the degree of
Master of Science in Cognitive Computing

Goldsmiths College
University of London

Supervisor
Dr. Marian Ursu

Department of Computing
Goldsmiths, University of London
New Cross, London SE14 6NW

September 21, 2012

Abstract

Tasks like retrieval, filtering and reconfiguration of digital video are difficult to solve using current computational techniques. An important cause of this difficulty is the semantic gap between visual representations and the meaning we address to them. A solution commonly sought in AI research is to reduce the gap by feature extraction followed by supervised learning of semantical concepts that are labelled to content. These methods often fail to work both reliably and generally on the unpredictable content found in the large video libraries of user-generated content that account for much of the internet traffic these days.

Another way of hunting down meaning in visual content is to step over the gap altogether and ask people for a meaningful interpretation one wishes to acquire for an item of content. By accessing many people's interpretations in small bite-sized tasks, collectively grounded annotations can be established. This form of accessing human computational power has seen a major increase in attention and application, for a large part because of the increased connectivity of individuals to the web and the surging amount of visual content that is uploaded to the web.

This thesis investigates how tasks involving meaningful interpretation of video content can benefit from the use of human computation. In order to test the validity of these approaches 'wePorter' is developed, a system with the purpose of finding local intervals of interest within videos in a set of topically related content. We also investigate how such a system can be used for reconfiguration of content into new and informative stories. We introduce 'parallel play' as a useful method for user interest elicitation in time-based media and present our results of reconfiguration of video parts, filtered based on users' attentional data. Initial user evaluation shows that the content selected by our filtering methods is evaluated as relatively interesting and preferable compared to segments that the system indicates as less interesting.

Contents

Chapter 1

Introduction

Someone looking to get a feel of a recent large-scale event, might turn to an online video platform where it is common practice for users to share videos of their recent experiences[13, 15]. Querying the video platform YouTube for “Burning Man 2012, this month” for example, returns a set of several thousand videos[2]. ‘Burning Man’ is a participatory festival in the Nevada desert that attracts over 50,000 attendees[1]. The festival’s participants not only collaboratively create a week long festival, but as the query shows, also record plenty of videos documenting their activities. With so much content to offer it becomes a challenging task to find a set of videos that collectively give an overview of the atmosphere at an event.

The video platform YouTube has grown incredibly since its launch in 2005 and accounts for a large part of global online traffic[15]. The amount of user-generated video content that is uploaded to the web is increasing to incredible proportions, but it is not just YouTube that enjoys a heightened popularity. Online video is booming and the increase in available content along with vast numbers of users sharing, searching and otherwise interacting with video online, demands effective methods for video analysis.

When regarding visual content, people perceive high-level semantical concepts that contribute to their overall understanding of the depicted material. Computers on the other hand commonly only have access to low-level features extracted from the digital content by data-driven techniques. It is hard for these computational methods to address the high-level conceptual interpretations perceived by humans. This discrepancy between low-level features and high-level semantical concepts is known as the ‘semantic gap’[54] and poses difficulties for computational approaches to visual interpretation.

Users engaged in tasks like video search are used to phrasing their queries in terms of semantical concepts. Even when content-based retrieval methods like ‘query-by-example’ are used, users are known to expect semantic similarity between different pieces of content, rather than similarity based on low-level features that is used by these methods[67, 55, 27]. These issues present fundamental challenges in computational approaches to video interpretation. Because the difficulties are inherent to the computational approaches that are currently employed in attempt to narrow the semantic gap, it might be an option to look at other solutions to bridge the gap.

Recent years have seen much enthusiasm for a new paradigm in computer science that is undoubtedly stimulated by the expanded connectivity to and increased functionality of web-based applications. The idea in ‘human computation’ is to combine the computational power of humans and computers to solve problems that are hard to conquer by digital

[1] `http://www.huffingtonpost.com/2012/09/02/burning-man-2012-attendan_n_1851087.html`

computation alone[64]. Human computation seems particularly apt for application to the medium of (online) video because of the different levels of semantical interpretations humans perceive in videos. Furthermore, the interactive online video applications prevalent on the internet may prove useful entry points for accessing human computational powers.

To explore the merit of human computational approaches, this thesis presents a human computation system with the purpose of finding interesting segments within videos and reconfiguring these into meaningful overview stories. We present an interface that uses implicit user feedback in the form of attention time captured during the presentation of two video segments in parallel. We use the interaction data thus acquired to make predictions of global interest in parts of videos and propose a framework for attention-based filtering of video content. Besides the implicit acquisition of users' attentional data, the framework is able to reconfigure segmented content based on analyses of the data. The system is evaluated in a series of user experiments aimed to show whether the filtering techniques indeed provide a distinction of content that correlates with user interest.

The thesis is structured as follows. The next chapter indicates challenges faced in tasks concerning computational video interpretation. We describe current methods to solve the problem and indicate why they are not satisfactory for the wide domain of user-generated video content that accounts for unprecedented amounts of data and traffic on the web. In chapter 3 the idea of human computation is introduced and hinted to as a possible solution for the challenges in meaningful video analysis. Chapter 4 presents 'wePorter', a human computation system that uses interaction data for attention-based filtering and reconfiguration of video segments. We report on the results of a series of experiments run on the wePorter system in chapter 5. A discussion of the work is included in chapter 6 along with a word on future directions. Finally, conclusions are presented in chapter 7.

Chapter 2

The Quest for Meaning in Video

2.1 Introduction

Interpreting moving images is not a hard task. The medium film is often described as ‘dictatorial’ because of the way the audience is immersed in a multi-modal experience, meticulously designed by the content’s creators. When watching a film, we sit back and relax, passively taking in the presented information without much effort. This ease is also reflected in our use of the word ‘couch potato’ to describe the passive role of television audiences. Watching film or video gives us almost immediate access to a wide range of information about what is presented on screen. We recognise objects on screen and understand words spoken in a language we know. We are also quick to infer a larger picture around the things we perceive, like personality traits of characters on screen and our emotional stance towards them. While most of these things happen extremely quickly and seemingly automatically to us humans, computers often have a hard time even starting to perceive a visual representation of an object.

When we attend to visual content depicting parts of the world around us, we can’t help ourselves from seeing its parts as separate entities. We recognise objects as if they stand out from their background even though they are simply patterns of colours on a two dimensional surface. To a computer, tasks like object segmentation and recognition are hard because visual information needs to be interpreted using some form of sequential processing. Digitally, images are usually represented by collections of numbers indicating local intensities (e.g. colour or brightness) at the different points that make up the image. How to calculate from this information, which objects are present, and what other concepts can be assigned to an image is studied in the field of *computer vision.* The tasks most related to finding computational interpretations of video content are video concept detection and video categorisation. Although recent years have seen important advances in the use of high-level semantical concepts in tasks like concept detection and concept-based video retrieval [56, 55, 67, 14], computational methods commonly have difficulties in performing both reliably and generally[60, 56].

Because of the elusive character of concepts like ‘meaning’ and ‘understanding’, goals for this chapter are kept intensionally modest. The intension is not to give an accurate explanation of daunting concepts like meaning or semantics, nor is it to give an accurate account of the diverse work on signifying systems such as has been done in the field of semiotics. This first chapter is meant to briefly introduce the difficulties that current computational methods have in arriving at meaningful interpretations of visual content. To this purpose we formulate a framework of computational interpretation of visual content that serves to establish terminology to work with in this work, rather than to make claims about the deeper functioning of human understanding or signifying systems. The next section addresses two high-level challenges to the goal of finding meaning in video and indicates how they arise. Of these, the *semantic gap* is the most poignant and we take a look at how computational approaches aim to overcome this problem. The chapter concludes by pointing out outstanding challenges and hinting at a different solution that might step across the semantic gap altogether.

2.2 Challenges in Computational Interpretation of Visual Content

As video content possesses most of its information in the visual stream, most research into the interpretation of video has focussed on the analysis of visual content [56, ch. 2]. To better understand what is going on in the interpretation of visual content by both humans and computers, it helps to model the process from start to end. Figure 2.1 shows in a high-level model how objects in the world are sensed and consequently rendered in a visual representation. We can think of this process taking place when we photograph a car and end up with a picture of that car as a result. When the representation of an object is next interpreted by someone, we can think of this person as establishing semantical concepts relating to aspects of the depiction. A situation to which this part of the model applies would be someone looking at the picture and recognising the car.

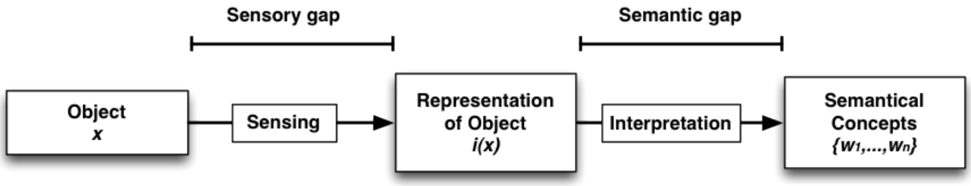


Figure 2.1: A high-level model of the interpretation of visual media content

A first source of complication in the process from object to its interpretation, is the *sensory gap*, described by Smeulders et al. as follows:

> "The sensory gap is the gap between the object in the world and the information in a (computational) description derived from a recording of that scene."[54]

The sensory gap makes accurate description of objects in the world difficult as it introduces uncertainty about what aspects of the object are represented. Characteristics of illumination, occlusion, clutter and camera viewpoint all affect the representation of a sensed object. When detailed knowledge about the recording conditions is absent, it is impossible to know which parts of the sensory information should be attributed to the state of the object and which are due to incidental artefacts. Different 3D objects can yield the same 2D representation and differently coloured objects might be represented by identical colour values. This also works the other way, as one object may appear very different in shape and colour on different images depending on illumination and camera viewpoint.

A second and more challenging issue that hinders meaningful computational interpretation of visual content is the *semantic gap* that lies between a digital representation and the conceptual interpretation we address to it. Snoek and Worring adapt the original definition from [54] to specifically fit the medium video when they describe the semantic gap as:

> "The lack of correspondence between the low-level features that machines extract from video and the high-level conceptual interpretations a human gives to the data in a given situation."[56]

The semantic gap makes automatic video categorisation and video concept detection difficult tasks[56]. It also makes it hard for users searching in digital video systems to formulate their query in a way that matches the features accessible to the retrieval system.

One of the causes of the semantic gap is that the way people interpret images is mostly contextual[54]. We look for concepts that are already familiar from our environment or earlier encounters with visual content. Our perception of a simple object is determined by our vast background of personal experience and cultural upbringing. In contrast to these contextual interpretations, computational image descriptions rely purely on data-driven features that can be extracted from the content. Difficulties arise when there is a mismatch between the two.

Another cause of the gap are interpretations that are subjective in nature. Semantical concepts relating to feelings and emotions can vary widely across different people. Deciding computationally whether concepts such as "romantic" or "funny" apply to a piece of content is hard when there is no agreement about the interpretation to begin with.

Perceived concepts are also combined to infer a larger story around the things we actually see. These knowledge-based interpretations enable us to perceive deeper layers of meaning that are not in itself explicitly represented. An important example of this is the way 'readers' of narrative texts or moving images combine elements in their aim for *coherence*[9, p. 38] [23, 24]. High-level concepts like coherence over time are usually not explicitly represented in digital content and can be hard to compute algorithmically.

Even if there is little context dependency in the perception or recognition of an object in video, it might still be hard for computational methods to produce appropriate semantical labels. This is due to the wide variety in appearance of visual concepts. Determining whether a clock is present in a video can be difficult because of the many different sizes, shapes and colours clocks can have.

All of these issues contribute to the gap between the low-level features extracted from video and the interpretations humans give to them. Challenges posed by the semantic gap are of mayor concern to the research community focussing on multimedia retrieval based on querying by user defined semantical concepts. The challenge is thus relevant to different scientific disciplines such as computer vision, information retrieval, machine learning and human-computer interaction. The next section briefly reviews computational strategies that aim to narrow the semantic gap.

2.3 Computational Undertakings of the Quest for Meaning

This section gives a short overview of strategies to narrow the semantic gap that is apparent in the computational interpretation of video content. At the core of this quest for meaning is the task of concept detection[56], where video clips are analysed to automatically detect whether a certain concept is present. Another step that is commonly taken to go from low-level video features to semantical interpretations is a classification of the type of content. This classification can be done at different levels, ranging from general and conceptually low-level (a scene containing music) to specific and conceptually high-level (a rock concert at an outdoor festival)[66].

Before starting the processes of classification or concept detection, videos are usually segmented into smaller clips. The most common unit for temporal video segmentation is the *shot*, one continuously recorded interval in the same setting of time and place. Shot segmentation is a well-understood problem and efficient automatic methods exist [71, 70]. Another form of partitioning is to segment the video into *scenes*, possibly consisting of multiple shots, signifying a unit within a story[66]. While shot segmentation can be done automatically thanks to data-driven procedures, the task of scene segmentation relies on semantical and narrative interpretations of the content and is thus a lot harder to solve computationally.

The tasks of video classification and video concept detection, are generally organised as follows. For a video segment or keyframe i, represented by n-dimensional feature vector x_i, a measure is calculated that indicates whether conceptual label ω_j applies to shot i (concept w_j is present in i or i can be classified as being of type w_j). The most common paradigm to find the relation between x_i and ω_j is supervised learning. Supervised learning methods use a large number of examples in a training phase to find an optimal combination of features that codes for the presence of a particular concept. Using the found relationship from features to conceptual label, previously unseen instances can be classified with a certain accuracy. This section briefly addresses different features that can be extracted from video content and explains the general framework of supervised learning.

2.3.1 Feature Extraction

Video content has a multi-modal nature, and may consist of a recorded visual stream, animations, recorded or synthesised sounds, spoken language and textual information in (sub)titles, all presented in a sequential format over time. This rich nature of the medium makes that there are many different types of features that can be extracted from a piece of content.

To help alleviate the semantic gap between low-level features and high-level interpretations, features should have enough discriminatory power to distinguish between the appearances of different concepts. Due to the sensory gap, variations in appearance also exist that are not caused by a difference in semantics, but are rather induced by the recording conditions. Features need so have a sufficient level of *invariance* to these accidental visual distortions introduced by the sensory gap[54]. A higher level of invariance in the description of concept w_j means the concept will be detected across a variety of different recording conditions. On the other hand the invariance might cause concept w_j to be detected in the representation of other concepts with a similar appearance. Invariance thus comes at the cost of discriminatory power. In the choice of a feature set a balance should be sought between invariance and discrimination that is suitable for the particular domain of content and application. Most focus in feature extraction is on visual features, and we will start by indicating the types of features that are in use.

Visual Features

Despite the different modalities that can collectively make up a piece of video, it's defining characteristic is the presence of a sequence of images. Most efforts to narrow the semantic gap in video systems focus on the visual modality and try to make use of the features that can be extracted from it. In their wide-ranging overview of concept-based video retrieval techniques, Snoek and Worring point to the following types of visual features that are used in video concept detection[56].

- *Colour* - Colour can generally be represented in different 3D colour spaces (e.g. rgb, hsv or $l * a * b$) and has discriminating potential superior to the single dimensional greyscale domain. In [54] Smeulders et al. indicate two aspects that have to be considered when working with colour features. First is the considerable variability in appearance of coloured surfaces under different recording circumstances, contributing to the sensory gap. Second is the intricacy of human colour perception that has to be accounted for in addressing visual interpretations approaching those brought forth in human experience.

- *Texture* - While colour features can be calculated for every pixel in an image, texture features look at regions of multiple pixels to determine local patterns. Texture features are used to describe different materials or surfaces, for example the fine grained texture of sand versus the linear texture of hairs. A common practice is to capture directional patterns of texture using localised derivatives of changes in colour[30]. An example application of such methods is the detection of edges within an image.

- *Shape* - When colours and textures of an image have been analysed, the resulting features can be used to partition images into smaller homogeneous areas. The shape of these areas can next be represented by features that either describe the shape's region or contour. Data-driven methods are used for *weak segmentation*, where an image is deconstructed into shapes that share a visual property[61]. *Strong segmentation* on the other hand, uses knowledge about the shapes of objects to delineate contours of semantic concepts in the image.

- *Temporal* - Besides addressing aspects of single video frames, visual features can also capture how characteristics of frames develop over time. By following how sequential images change over time, patterns of motion can be tracked to describe camera motion[57], motion of regions or points [51] or even the movement of segmented objects[45]. A problem with using temporal features is that they are computationally costly and time-consuming to extract. This is a general problem with video induced by the sequential nature of consisting of information rich images. Because of this, temporal features are not commonly used in automated detection and categorisation methods.

Auditory Features

While video semantics might be most prominently expressed in the visual domain, auditory signals can also be used for segment-type classification and concept detection. In fact, auditory features may have the important advantage of being computationally cheaper relative to their visual counterparts. Considering this benefit, it can be strategic to start with an initial analysis of audio signals, and only proceed with more costly video analyses if further disambiguation is required. Different types of audio signals can be used for analyses

As is the case for visual features, video content is first segmented before audio features are extracted. Generally, auditory feature extraction is done on two levels: short-term frame level and long-term clip level [66]. Frames are usually very short sample intervals spanning 10 to 40 ms, for which auditory signals are assumed to be stationary. Clips have longer durations that span multiple frames and are used to capture the changes in frame features over time.

In their overview of the merit of audio and visual features in the characterisation of semantic content, Wang et al. categorise audio features based on the type of information they are extracted from. They distinguish features based on *volume*, *zero crossing rate*, *pitch* and *spectral features*. Description of these features and their respective merit are left out of this thesis. Interested readers are referred to [66] for a detailed explanation. With frames analysed, features at clip level can be calculated to reflect the changes in frame level features over time. The different types of features on clip level can be characterised by the categories of the frame level features they are based on.

Textual Features

So far we've seen that auditory and visual information need interpretation to arrive at semantical concepts that can be expressed in text. In contrast to the sensory nature of audio and visuals, textual data is nice to deal with computationally as its symbolic nature makes it directly accessible to algorithmic processing. Not all videos feature text, but for certain types of video it is a viable option to extract textual information and use it for the characterisation of the video's semantics. Digital video files in itself do not contain textual data, but this can be extracted either from the visual or auditory stream.

Text might be available in a video's visual content in the form of titles or captions. It is mostly structured content, produced by a (semi-)professional editor that has these kinds of texts embedded. Video content following a fixed structure has the additional benefit of text elements appearing at regular times and positions. News programmes for example feature titles at fixed moments in time such as during the introduction of a person or location. *Video optical character recognition* has been applied to news material to transcribe headline texts indicating topics of news items as well as to extract information about the text such as size and position[39].

Another form of text from video is the transcription of spoken language in the audio stream. This is particularly interesting for video content that contains much information in spoken language, such as news programmes or other narrated presentations. For such content transcriptions may be present in the form of closed captions or extracted using *automatic speech recognition.* Accurate transcriptions can lead to major improvements in interactive retrieval performance by novice users[17].

2.3.2 Supervised Learning

Once a suitable set of features is extracted for a collection of videos, they can be analysed to see how they relate to the concepts that are detected within the videos. The paradigm of supervised learning looks to find a relation between features describing data instances and classifications that can be attributed to them. Supervised learning takes place in two stages. In the initial training stage, a large set of training examples is taken along with the known classification or labels of the content. Different methods can be used to determine a function that optimally describes how features are combined in the calculation of a measure that indicates whether the concept is present. During the testing stage the trained model is used with new instances as input (represented by the same set of features as the training examples) and calculates the probability $P(w_j|x_i)$ of concept w_j being present in the video segment i represented by feature vector x_i.

Although detectors can be trained to detect patterns of multiple concepts, usually separate concept detectors are trained for distinct concepts. By applying multiple detectors on an previously unseen input instance, multiple concepts can be detected.

2.4 Outstanding Challenges

Despite significant advances have been made in recent years in methods to narrow the gap between low level video features and the high-level interpretations humans address to the content, the semantic gap still forms a major scientific challenge. The computational methods described in this chapter have clear values in addressing the semantic gap, but there are several difficulties that make it unlikely for the the gap to become bridged completely soon.

Although the low-level features described here can all be extracted automatically, the use of supervised learning methods still requires initial labelling from trusted sources. Acquiring these initial human labels might be costly and time-consuming.

Related to this is the idea that for accurate interpretations, a system might have to be updated to reflect newly added content or the latest contextual knowledge of its users. Periodical reassessment of feature sets or user-defined labels may prove impractical in an architecture based on supervised learning.

Processing visuals is a complex matter in its own right, but the temporal aspect of video adds an extra dimension of challenges. The sequential nature of video makes it a very information rich medium, with much to gain from but also much to be challenged by. Looking at temporal features is costly and therefore currently left largely unexplored.

Even though the combination of low-level feature extraction and supervised learning builds a bridge across the semantic gap, these methods leave many intermediary levels of interpretation unaddressed. Of particular importance seem to be narrative analyses that characterise scenes within a video according to the role they play in a story. These features are very conceptual and thus hard to detect automatically by data-driven procedures based on low-level features. A second difficulty comes from the fact that characterisation of these concepts is hugely dependent on the context in which they are presented. Because narrative structure arises from sequential ordering of elements in time, it requires analysis that addresses a range of shots or scenes which is problematic because of aforementioned reasons. It has been shown that the configuration of elements in film and video can strongly affect the meaning that emerges from their assemblage. This property is dealt with extensively in studies of cinema[9] and is termed the 'Kuleshov effect', after Lev Kuleshov who is an early investigator of this dependency effect:

> "one must not forget that the location of the shot in a a montage phrase is crucial, because it is the position that, more often than not, explains the essence of the meaning intended by the artist-editor, his purpose (often the position in the montage alters the content)."[38, "The Principles of Montage"]

Perhaps the biggest challenge in the automatic interpretation of video is the wide variety of content that is produced and distributed nowadays. When considering "*narrow domains*" of visual content, variations in appearance across different concepts are limited and predictable[54]. This makes narrow domains relatively easy to interpret as accidental distortions due to the sensory gap are limited. The contrary is true for broad domains:

> "A broad domain has an unlimited and unpredictable variability in its appearance even for the same semantic meaning."[54]

The broader the domain, the wider the semantic gap. Phrased in the context of image retrieval, Smeulders et al. further illustrate the idea of broad domains by mentioning the set of images available on the internet as the broadest class available. The same can be said about video. Regarding the enormous amount of user-generated video content that are being uploaded, a platform like YouTube comes frighteningly close to this broadest scope. With so many users actively participating on such large scale platforms, extremely broad domains of video content become realities to be dealt with appropriately and this may prove a hurdle in the effort of solving the problems posed by the semantic gap.

Alternative to the approach of unleashing advanced number-crunching algorithms to try to achieve more meaningful interpretations computationally, there may be other ways that alleviate the problems posed by the semantic gap. The next chapter looks at methodologies that have at their core the idea of accessing people's interpretations to support digital systems in tasks that are currently hard to solve computationally. Considering the outstanding challenges due to the semantic gap in automatic video interpretation, these methods may prove especially rewarding for the medium of digital video.

Chapter 3

Human Computation

3.1 Introduction

In his seminal paper 'Computing Machinery and Intelligence' Alan Turing proposed what he called an imitation game, to answer the question "Can machines think?"[58]. The game involves a digital computer running an advanced programme and a person who each take place in one of two rooms randomly. A human interrogator to whom the position of computer and person is unknown, is given the ability to communicate back and forth with the inhabitants of the rooms by textual messages. It is the interrogator's goal to figure out which of the rooms houses the computer and which one the person.

The game is now known as the *Turing Test* and is still considered a method to determine a programme's capacity to 'think' or display a human level of intelligence. Turing's proposed experiment raises the question whether human thought can be expressed in terms of *computation*. The Turing Test indicates how certain tasks may be trivial to human beings but prove extremely challenging to computers. The task proposed by Turing is considered to rely on such a wide range of the human intellect that its successful imitation by a machine is taken as indicative for computational mastery of human thought.

In the same paper, Turing explains the idea of a digital computer by relating its activities to those that can be carried out by humans:

> "[t]he idea behind digital computers may be explained by saying that these machines are intended to carry out any operations which could be done by a human computer"[58]

The notion of 'human computer' asks for some contextualisation, as in the last few decades we've become unaccustomed to the term. Human computers were not uncommon in the time of Turing and before that from the 18th century, when 'computer' was used to simply signify 'one who computes'[25]. People bearing the function title were involved in the execution of calculations produced by strictly following mathematical theories. The activity that these computers were involved in were processes of rote, not requiring any human creativity. While working on the design for the first ever mechanical computer, Charles Babbage refers to it as "mental labour"[5, Ch. 20].

The idea that some tasks are hard to express in computational terms but easily solved by humans has received much attention in recent years. *'Human computation'* as an academic paradigm saw its development sparked by a doctoral theses by Luis von Ahn in 2005 and has seen an increase of attention since that time[48]. The main idea in human computation is that certain tasks that are too hard to solve by current computational techniques, may be solved by the combined effort of humans contributing their cognitive skills.

In a recent survey paper, Quinn and Bederson present a taxonomy of human computation [48]. They sketch the trend of this new paradigm for intelligent problem solving by pointing at the increase of academic papers featuring the term 'human computation' and its relative 'crowd-sourcing'. They summarise a myriad of definitions given in recent works by different authors in two key points about the nature of *Human Computation Systems* (HCS) and the problems they intend to solve:

- "The problems fit the general paradigm of computation, and as such might someday be solvable by computers."
- "The human participation is directed by the computational system or process"

3.2 Characterising Human Computation Systems

To be able to analyse the merits of different approaches in the paradigm of human computation, it helps to have a characterisation of the different components that generally make up a HCS. Quinn and Bederson present such a framework in [48] and use six dimensions to distinguish different types of systems: motivation, human skill, aggregation, quality control, process order and task-request cardinality. We briefly discuss these factors below and then propose our own general framework to describe the functioning of an individual human computation system. We will use the proposed concepts in the description of our own human computation system in chapter 4.

3.2.1 Comparing Human Computation Systems

Motivation

As we saw in the previous chapter, it is often difficult or costly to acquire accurate human-contributed data. Motivating people to participate is one of the main challenges in the design of HCSs. To ease a user's entry into participation, tasks are often presented in short bite-size chunks and made easily accessible over the internet. But as the tasks at hand do not directly benefit contributors, they will need to have a strong motivation to contribute their time and cognitive resources.

Different kinds of motivations can be engineered into a system, as long as they provide users with "a reason why doing the tasks is more beneficial to them than not doing them"[48]. Quinn and Bederson include the following types of motivations:

Pay - Participants can be paid by money or other resources[8]. Amazon's Mechanical Turk[1] is an 'online crowdsourcing marketplace' that utilises monetary payments to participants contributing their time to small computer directed tasks. The platform has received attention from different research communities[10, 46, 37], which has in turn lead to critique about neglected limitations of the platform[4].

Altruism - Users may be motivated by the wish to simply do good, especially when they feel the problem being solved is interesting or important.

Enjoyment - The abundance of entertainment activities such as games and media consumption platforms available online show that web users often spend much time

[1] www.mturk.com

in pursuit of enjoyment. Making a human computation task enjoyable can motivate users to participate and have a good time in whilst contributing their human skills. A group of HCSs that rely on this kind of motivation is termed 'Games with a Purpose'[65] and channels human behaviour by the motivation of gameplay. An example is the ESP game used to acquire meaningful image labels[62].

Reputation - For tasks associated with an organisation or platform that has a certain level of prestige, participants may be motivated by the idea of their contributions being showcased on as part of their profile.

Implicit work - There are already many interactions taking place in different web environments. If a human computation task can be mapped to the configurations of such a preexisting activity, users can participate without engaging in any extra effort than they are already used to. Forms of implicit work could even be so much intertwined with existing activities that users might not even be aware they are contributing they cognitive skills to a higher purpose. ReCaptcha[2] is a successful example where the human transcription of scanned books parts that are hard to decipher by optical character recognition is incorporated in the existing activity of solving a 'captcha' to access a free email account[63].

Human Skill

Another salient factor in the characterisation of HCSs is the type of skill humans contribute in the task they are presented with. Examples of human skills required in different systems are visual recognition [62, 63, 18], understanding of natural language[7][28] and music interpretation[40].

It is interesting to note that all of these tasks reside in the high-level conceptual realm of semantic interpretations. This relates back to the semantic gap for visual content and the general difficulty of deriving meaningful interpretations from low level features of multimedia content. Considering that human computation intends to solve problems that are too hard to solve by current computational techniques, it comes as no surprise to see the challenging tasks from chapter 2 resurface here.

Aggregation

Most applications that use human computation distribute large numbers of small tasks to many individuals. Sometimes the results of these task directly contribute to the problem that is being solved, but often they need to be aggregated in order for this to happen. Mechanisms of aggregation that may be used include collection, statistical processing of data, iterative improvement, active learning, search, genetic algorithms[48].

Quality Control

Working with data from a large number of volunteers or non-experts, may lead to distortions in the data caused by misunderstanding of the instructions. Another issue is the existence of malicious spammers contributing wrong answers [29]. To yield useful results from people's computations, these unwanted data need to be accounted for. Different procedures exist to counter this problem, some of which focus on the setup of the interaction (e.g. design of the rewards system[44], input agreement[40] and output agreement[62]),

[2] http://www.google.com/recaptcha

others on analysis of the result after data is contributed (e.g. comparing redundant contributions to the same task, statistical filtering, expert reviews and automatic result checks).

Process Order

Process order describes the configuration of three main roles in the HCS[48]:

Requester: "The end user who benefits from the computation (i.e. someone using a n image search engine to find something)".

Worker: The person performing the computation.

Computer: The digital computer system, only considered to be active "when it is playing an active role in solving the problem, as opposed to simply aggregating results or acting as an information channel".

Task-request cardinality

Human computation systems can have different numbers of interacting users. On the side of the workers, many people's contributions may be aggregated to serve a single or many requests. Although not common, it is possible that a request is handled by a single worker, without any aggregation. Considering these different possibilities, Quinn and Bederson give examples of the cardinalities "One-to-one", "Many-to-many", "Many-to-one" and "Few-to-one".

3.2.2 Describing a Human Computation System

The generic analyses proposed in [48] are useful for the comparison of different systems as they seem to capture in a concise way many aspects these systems have in common or set them apart. They are good for a broad characterisation and categorisation of systems, but lack the expression to talk in detail about what constitutes a specific system. For this reason we propose the combination of *'purpose'*, *'motivation'* and *'task'* to help in the conceptual description of a human computation system. The concepts are closely linked to the distinction of the three roles of "requester", "worker" and "computer" made in [48]. Our proposed concepts though, focus more on the functionality of the system rather than merely pointing to components. In chapter 4 we propose our own system and use these concepts in its description.

Purpose

Any human computation system is aimed at finding the solution to a problem. Perhaps bordering the obvious, the first level of description of a system is the precise indication of the problem being solved. Pointing to the effort that is commonly required by multiple contributors in order to solve a computationally challenging problem, we prefer the term *'purpose'* over 'problem'. The purpose of a system is linked to the functionality desired by Quinn and Bederson's *requester* but can be thought of at a larger scale. While a single requester in the ReCaptcha system might for example be interested in the accurate transcription of several books, we can indicate 'the digitisation of books from Google Books' as the larger purpose served by the system.

Motivation

A comprehensive description of motivation is given in our discussion of Quinn and Bederson's characterisation. A precise study of user motivation will help the description and design of any HCS. Motivation is tied to the role of the *worker* as it defines the reason to contribute work to the system.

Task

Finally a description of a HCS should include a detailed description of the task presented to the worker along with information about how user-contributed data is being acquired and subsequently processed. The task forms the most technical level of description and is related to the role of the *computer*. Task descriptions should indicate how the computer is involved in the direction of user interaction towards the purpose that is addressed in the system.

3.3 Bypassing the Semantic Gap?

Several aspects make the paradigm of human computation well-suited for application to tasks concerning meaningful video interpretation.

In general, many of the problems that are currently hard to solve computationally are related to finding meaningful interpretation of digital content. This is true for music interpretation, understanding of natural language as well as visual recognition and interpretation. Visual interpretation may stay a challenging task for a longer time because of the sensory nature of most of the information present in videos and people's high level narrative interpretations that are specific to video because of its sequential nature.

The wide domain represented by the increasing amount of user-generated video content that gets uploaded to the web will furthermore present challenges in tasks like retrieval and recommendation. On the other hand, the incorporation of this content in online video sharing platforms, means that popular content is frequently interacted with. These existing interactions may be used to leverage the motivation by implicit work in human computation applications directing users' interaction data to serve a larger purpose relating to video interpretation.

We have suggested the paradigm of human computation as a viable option to make video content more accessible to computer systems and thereby indirectly to their users. It should be noted that in pointing to an alternative solution to the problems raised by the semantic gap, intensions are not to point away from the strategies described in chapter 2. These methods have achieved promising results and shown much improvement in recent years. Considering the first point in Quinn and Bederson's definition of human computation, we can maintain hope that new or improved computational approaches will continue to narrow the semantic gap.

Chapter 4

Human Computed Stories in wePorter

4.1 Introduction

This section describes the interaction design of the *wePorter* system, built to exemplify how the paradigm of human computation can be used in tasks like filtering of video segments and semi-automated video reconfiguration. The system derives its name from the idea that many people interacting with a human computation system, may be able to collectively produce meaningful overview reports from a large set of user-contributed video content of large scale events.

The wePorter system runs an interactive webpage that functions as the main source for data acquisition, presentation of results and general proof of concept. In this chapter the system is analysed along the axes of *purpose*, *motivation* and *task*, that were introduced in the analysis of Human Computational Systems in chapter 3. Next to these guidelines for analysis, remarks are made about the specifics in the functioning of the system. Lastly we discuss the implementation of the web application that is central in wePorter.

4.2 User-Generated Video Content

> "Since the dawn of YouTube, weve been sharing the hours of video you upload every minute. In 2007 we started at six hours, then in 2010 we were at 24 hours, then 35, then 48, and now...60 hours of video every minute, an increase of more than 25 percent in the last eight months. In other words, youre uploading one hour of video to YouTube every second. Tick, tock, tick, tock thats 4 hours right there!"[1]

These astonishing figures of the amount of video that is uploaded to YouTube are nothing short of mind blowing, but will most likely sound dated in a matter of years or even months. Looking at the increase of content uploaded to the video platform in past years, the growth does not seem likely to come to a halt soon. All these videos are great for online video junkies, and are increasingly part of the online journalism landscape [49]. At the same time, all these videos being put online beg the question which ones of them to watch.

[1] http://YouTube-global.blogspot.co.uk/2012/01/holy-nyans-60-hours-per-minute-and-4.html

The increasing amounts of user-generated video content (UGVC) being put online, lead to an information overload and present both challenges and opportunities in search, retrieval[59] and recommendation[72] tasks. There is an increased need for ways of aggregation and filtering. Both of these tasks rely heavily on an at least a shallow understanding of what is presented in these media, which, as we've seen in chapter 2, is a hard problem to solve via current computational techniques. With so much content being uploaded, how can we find our way in the already enormous ocean of online videos?

4.3 The Purpose

With more than an hour of new content per second it is no wonder that YouTube has come to be viewed as the go-to for online video, much like "the digital video repository for the Internet"[2] that was envisioned by its founders in their first official blog post. An important activity on video platforms like YouTube is searching and much work has focussed on video retrieval[41, 55, 17, 26, 34, 27, 21, 56, 53]. We review the different aims in users' interaction in video retrieval tasks and point to an aspect of video retrieval that has not received much attention in recent research. This is the challenge of segmented video recommendation which forms a task we address in wePorter.

4.3.1 Different Aims

Annotations reflecting the content of a video can, along with other meta data of the video, be used for retrieval of videos in response to textual queries. The effectiveness of such a retrieval task varies depending on the information that is used in the search algorithm and the type of content that is searched for [27]. A third characteristic that determines the effectiveness of a video retrieval system is the goals that users have in their usage of the system [27]. User goals can vary widely from more to less specific[19]. We expand on this latter point, as it forms an important context for the wePorter system.

Direct Navigation

The most specific goal is exemplified by a user who is drawn to a video platform by a direct link from an external website. Links can either be in the form of actual hyperlinks or playable embedded videos that are followed through to the platform. Navigations via such links form a direct mapping between a user's intention to the desired piece of content. In this case, users have a very specific reason to come and watch. Their desire, at least of knowing the contents of the video, is satisfied after the viewing. YouTube's system engineers call this way of video viewing *"direct navigation"*[19].

Search and Goal-oriented browse

When users have not obtained a direct link to a potentially relevant piece of content, they might still have a specific goal in mind when visiting an online video platform. Reasons to visit might be the wish to see a particular music video or to find an instance of a series by a particular producer. This goal of discovering a rather specific video is referred to as *"search and goal-oriented browse"*[19]. Provided that the desired piece of content exists and the video platform has an appropriate search function in place, these 'narrow queries', will result is a result set of search results from which the user is likely to handpick the

[2] `http://YouTube-global.blogspot.co.uk/2005/07/greetings-everyone-thanks-for-visiting.html`

sought-after result fairly quickly. Here the user's desired result often lies within a single item of content. Perhaps a few misses are required, but after a couple of clicks the user hits the desired video.

Unarticulated Want

Yet a less specific goal is seen in users who come to a video platform "to just be entertained by content that they find interesting" [19]. These users mainly browse from one piece of content to the next, often aided by the platform's recommendations of related content. It has been found that YouTube's related video recommendation functionality, which recommends videos that are related to the video currently being watched, is one of the most important view sources of videos. In fact, traffic received from these recommendations is the main source of views for the majority of videos on YouTube [72]. Features derived from users' navigations such as 'click-through rate' have been used to improve content-based video recommendation [69].

Goal of a person's query in this kind of navigation is no longer defined in a single returnable item of content or even a containable set of items. Rather, the interactive pathway through the a set of interesting bits of content is what represents a user's aim. This broader, exploratory goal of finding different parts of interesting content has been termed 'unarticulated want'[19].

Encapsulated Wander

Considering the three categories of user motivation above, another, composite motive can be thought of. Users often start with a query for a particular topic, followed by a journey across many videos relating to their search term. Their navigation seems unarticulated but it is encapsulated by the topic of their query. Think of someone who wants to get an overview of a large music festival she recently attended. Big events where many people record videos, are often massively covered on UGVC platforms, resulting in an overload of visual information. Searching YouTube for this month's videos from the participatory festival Burning Man, two weeks after it ended, returns "About 7,660 results"[2]. A similar large set of topically related UGVC can be imagined at a website that asks participants to contribute their videos recorded at a recent event or centred around a particular topic.

This kind of 'broad queries' returns a result set of related content in which a user will probably consider many items as a successful retrieval. Furthermore, one could even say that the desired result of a user's query is spread across the multiple pieces of content. By traversing the space of different videos in the result set, users interactively construct the desired answers to their own queries. We call this motivation for discovery within a topically-related set of videos 'encapsulated wander'.

Interactivity is generally agreed to play an important role in the task of video retrieval, as is reflected by the separate category in the annual TRECVid challenge for interactive video retrieval[52]. Several works have indicated the importance of interactivity in the task of video retrieval to filter through a set of initially returned results [20, 16, 20, 21]. While most of these systems are aimed at retrieval of clearly specified queries, exemplified by the TRECvid retrieval task, the need for interactive exploration is even more apparent for the broader oriented goal of users engaged in 'encapsulated wander'.

4.3.2 Serving the Purpose of Encapsulated Wander

The answer to a user's query now lies as much in the journey through the content as in the returned content itself. By traversing from one piece of content to the next, users construct a sequence of concatenated items. This self-constructed story is an important concept that wePorter capitalises on, as will soon become apparent.

The task at hand of recommending a larger group of interesting videos is radically different compared to the more narrow queries that could be answered by a small set of true positives in an information retrieval task. Besides the spread of the searched for result across different pieces of content, there is a second important difference that lies in the nature of the majority of UGVC.

User-contributed videos commonly consist of raw, unedited footage. In [49] Rosentiel and Mitchell report that within the collection they investigated only 39% of the news-related footage contributed by citizens was edited. It should be noted that this collection contained only the most popular videos per week and that a different distribution will be found in the complete set of news-related videos or all the videos hosted on YouTube.

Users with broad expectations will not only want to be presented with multiple relevant items from a complete repository, they are also looking for the most interesting parts within these relevant items. This issue is particular to time-based media, and especially relevant for video. Other temporal media, like audio in general and music in particular, have less of a need for segmentation because of their common usage in multimedia applications. People usually tend to listen to a song entirely and if they which to experience an album in part, constituent songs are already units on their own that can easily be reconfigured. Tag-a-tune is a game with a purpose used to acquire tags for clips of music. Although it could be employed for labelling of smaller audio sub-clips within songs, the games only aims at global labelling of a sounds[40].

Because of the unstructured nature of the majority of UGVC it is desirable to establish local recommendations that point to 'sub-clips' within a video that are of particular interest. Whereas digital music albums shared online consist of a collection of songs that can each easily be made to stand alone, video currently suffers from a less malleable identity online. Online videos are currently much like black boxes that can be played, paused, rated, commented on, tagged and shared only in its entirety. What if a piece of raw, unedited UGVC features something spectacular for ten seconds halfway along its timeline, but shows much of the same for the rest of the time? Answering this question is the first purpose of the wePorter system. The second is to serve the desire of wandering users for an overview in the form of a sequential ordering. Our specific aim is to supply users with a reconfiguration of the interesting video segments.

The ten significant seconds in a two-minute video become a needle in a haystack when an initial set of videos relating to your query includes hundreds to thousands possibly relevant videos with lengths between some tens of seconds and a couple of minutes. The aggregation and reconfiguration of several of these 'needles' into a meaningful new whole is another non-trivial task. We present wePorter as a test case for new methods that address both these issues of information overload in video libraries of UGVC. More precisely, wePorter's purpose is two-folded:

From a set of topically related unstructured user-generated videos:

1. Filter localised intervals (in time) of global interest (across multiple users) within each video within a set of source videos.

2. Reconfigure interesting video segments into a meaningful new story

In order to find local regions of global interest in videos, we assume there is a correspondence in the judgements of different people as to what parts of a video are most interesting. This assumption will not hold for video content in general, but might be reasonable for the unstructured UGVC we address in wePorter. Many videos that belong to this category have intervals where a particular action or event takes place, surrounded by additionally recorded material featuring little activity that is not edited out. One of the intensions of wePorter's current implementation is to see whether distinctions can be made between on this coarse level of preference.

4.4 The Motivation

How to get a group of unrelated people to contribute their efforts to solving the tasks set in our two-folded purpose? This section looks at the reasons people might have to contribute their computational powers to a system with a purpose like wePorter. Looking at the way people engage with online video content on platforms like YouTube, we identify patterns in their behaviour that can be matched to a task in a human computation system. This behaviour that is characterised by a more active role in multimedia consumption, can be seen as a larger trend in the development of new media. The end of this section indicates how the motivations of users of the wePorter system can link in with this larger trend.

Jain and Hampapur indicate entertainment, information or communication as purposes for the creation of consumer videos [31]. Although most UGVC is probably not as purposefully produced as the professional productions that Jain and Hampapur report on, these different purposes give an indication as to what user's motivations might be when interacting with a video system.

4.4.1 Information Provision through Online Video

Since the proliferation of mobile video recording devices, it has become common practice for large-scale (semi-)public events to be covered by UGVC that gets uploaded to the web. While some are critical[33] to the often heralded democratisation and empowerment of people by the new media production and distribution tools, it is clear that the UGVC at places like YouTube attracts a lot of traffic from people looking to be informed about recent events. After all, UGVC can have its advantages over traditional media when it comes to video news coverage, especially for unexpected events where traditional media do not have the immediacy of user-generated 'reports' recorded by coincidental passersby.

In a recent study as part of the the Pew Research Centers Project for Excellence in Journalism, the most popular video's from YouTube's 'News and Politics' were analysed for a period of 15 months[49]. The authors of the study exemplify the power UGVC can have in news provision by showcasing frequently viewed videos detailing scenes from the earthquake and subsequent tsunami that hit Japan in March 2011. The week following the disaster, the 20 most viewed news-related videos on YouTube all related to the catastrophic event and were together viewed more than 96 million times. Most of these videos were recorded by individuals who happened to be in the affected areas when the disaster struck, either uploaded by themselves, or by TV channels who appropriated the content. The study furthermore reports that in the studied period, the most searched term of the month on the YouTube platform as a whole was a news-related event 5 out of 15 months.

While the journalism study above focusses on videos with the 'News & Politics' label, information provision about current events might span a larger set of categories. Someone looking for footage in order to get a sense of the atmosphere at a recent music festival or public demonstration, might very well find relevant videos in categories like 'Entertainment', 'Travel & Events' or 'Nonprofits & Activism'. Across all of these categories, we are able to find examples of vast collections of UGVC, uploaded in the period following up newsworthy events.

4.4.2 Informative Entertainment

The wePorter system focusses on these kinds of topically related sets that people are currently exploring interactively by browsing from one video to the next. This way of navigation is an intermediary between the goals of *goal-oriented browse* and *unarticulated want*. The apparently aimless browsing is now encapsulated by the event but users still roam freely within this topicalised set of content. By navigating from video to video, watching some and skipping others, users leave attentional traces that might give valuable insight into their intentional standpoint.

It is this kind of interactions that are already taking place at a large scale that we like to make use of in the wePorter system. Motivated by the wish to explore informative content, users will instinctively and implicitly contribute their human knowledge to a system that is set up appropriately. This kind of motivation fits the category of ‘implicit work’ as it involves activities that people already engage in for their own reasons [48]. Considering users’ wish to be informed and the interactive way in which they navigate, there is most likely also a factor of entertainment involved. We expect that the more specific motivation of information provision might show to become a valid categorisation for the motivation of people in a HCS as it is a common activity on the web and inherently linked with the hard problem of meaningful interpretation of content.

4.5 The Task

In this section we take a look at how the larger goal of finding intervals of regional interest across time within a single video can be branched out into bite-sized tasks executable by a person in a single interaction. We begin by introducing some conceptual considerations that influenced the interface design. Then a detailed overview of the wePorter web interface is presented. We end with a section focussing on the implementation of the system.

4.5.1 Design Considerations

Below are included several points that have been instructive in the development of the interactive task central to the wePorter system. Some of these point are system requirements, others are more guiding design principles or thoughts that have been inspiring and formative in the development.

wePorter is a web interface

The power of a HCS that relies on data from many interactions is truly unleashed in an online setting, where many people can easily participate and interact. For this goal alone already, wePorter must be a web-based system. Besides the obvious choice of staying in the realm of the online video content, it makes sense to embed the theoretical explorations of this research in the practicalities of current web technologies. With the ongoing development of technology like HTML5, many new possibilities for a user’s web browser are unleashed. The implementation of a research tool concerning online video is a good opportunity for the exploration of the technological possibilities of present day web technologies.

Hypervideo

The power of digital content on the internet lies for a great part in its capacity to be hyperlinked. Linking to externally hosted content alleviates the burden of having to host or recompile pieces of media. Instead, files can be played and remixed by reference, leaving their respective sources intact and where they are. In the presentation of their digital video repurposing system 'Diver', Pea et al. indicate the advantages of using a virtual camera controlled by XML-based files that reference parts of source video instead of rendering new video clips[47]:

- "Virtual video clips eliminate the generation of redundant video files, greatly reducing disk storage requirements."
- "No rendering time means vastly improved performance. Users can instantly create and play back dynamic path videos without long video-rendering delays."

An implementation of a system where users interact with content that is dynamically reconfigured in real-time will benefit considerably from a hyperlinked functionality, especially when this takes place in an online setting where bandwidth will be limited.

The idea of hypervideo in the context of interactive narratives has been proposed by Sawhney et al., where users were invited to navigate a virtual cafe by means of *temporal* and *spatio-temporal* and *textual* links present in the video interface. A temporal link is "[a] time-based reference between different video scenes, where a specific time in the source video triggers the playback of the destination video scene"[50]. wePorter utilises temporal links to link sequences of video scenes together.

Localised Interest

To answer to the first purpose of wePorter, we wish to distinguish parts of videos based on their level of interest. In order to elicit users' preference for particular parts within a video, we divide each *'source video'* in our initial set of topic-related content into smaller *'video parts'* and present a selection of these in a user interaction. Slicing up source videos virtually and playing their parts by reference is made possible by a hyperlinked implementation of the video player.

Implicit User Feedback

The user interaction design should enable means to learn about a user's interest in a video at a particular moment in time. This to the purpose of discovering localised regions of interest within separate videos. To make a user's interaction as enjoyable as possible, implicit data acquisition should be preferred over explicit questions. In other words, user will be more likely to repeat a task that implicitly logs their behaviour during interaction, than one where they are presented with a questionnaire after every click. By making the acquisition of user feedback an integral part of an interaction, users are directed into contributing their computational power without even being aware of it. In wePorter, this enables *'curation through interaction'* by using the *'implicit feedback'* to maintain and improve a dynamic story space.

Capturing Attention Time by Parallel Play

Considering measures that could indicate how people's interest varies across different videos, an idea that quickly surfaced is that interest is closely linked to attention. When a piece of content contains something that is interesting to many people, this will most likely result in an increase in views, provided the content is accessible to a variety of people. This simple notion is the idea behind global recommendations that show most popular or ‘trending’ content. Whether the trending item is a video on a sharing platform or a phrase on a microblogging service, when there is a large number of people attending to it, this is a reason to suspect the item to be of interest for people who haven’t engaged with it yet.

An obvious limitation of these global recommendations is the lack of personalisation. Personalised recommendations are offered because the content that is globally popular may not be related to the topics of my interest. For the purpose wePorter is serving however, focus around a particular topic is already in place and we are in the first instance mostly interested in picking out the parts that share a high level of interest globally. The experiments described in chapter 5 are thus not focussed on personalisation.

The use of attention time for implicit user feedback is relatively new and its relation to interest and preference is still being investigated in research. Results of Kelly and Belkin are critical to the effectiveness of attention time as implicit feedback [35, 36]. Their work reports no “significant relationships between display time and usefulness judgments for the subjects in [the] study”. Furthermore they warn about substantial differences in users attentional behaviour and the dependence of their behaviour on the specific task the user is involved in.

The assumption that attention time may indicate interest is used in [68] where methods of predicting a user’s interest in online documents, are based on the time the user has spent attending to previous documents. Xu et al emphasise the need for personalisation in content recommendation as well as their method’s advantage of allowing for implicit user feedback through the use of commodity eye-tracking.

The wePorter system uses a method of user preference elicitation similar to that of [68], that makes choice of attention an integral part of the user’s task. User’s make explicit choices in their attention but their feedback is captured implicitly in the interaction. A web interface presents a user with two concurrently playing videos for which we would like to elicit preference. The user is forced to make an explicit choice of focussing on one video or the other. During this ‘parallel play’ of two video parts we capture the amount of time focussed on each of the parts resulting in the pair $\{focus(i_1, u_j), focus(i_2, u_j)\}$ of user $u_j\acute{s}$ focus on video segment i_1 and i_2 expressed in the time spent focussing on the respective segments. This paired data is stored for later analysis. The method of parallel play may prove useful especially in eliciting preference for time-based media like audio and video as the time users attend to an item can be easily incorporated in existing interactions, thus matching the motivation of ‘implicit work’ mentioned in section 3.2.

Recurrent Interaction

Because of the reliance on data, user’s should be able (and encouraged) to engage in the interaction more than once.

Users Between Consumers and Producers

Studies reflecting on new media technology and its incorporation in our everyday life are in recent years often speaking of a media convergence, where multimedia content flows dynamically across multiple media platforms and media audiences take an active, participatory role in their search for entertainment experiences. In his book ‘Convergence Culture’, Jenkins writes:

> “This circulation of media content - across different media systems, competing media economies, and national borders - depends heavily on consumers’ active participation. I will argue here against the idea that convergence should

> be understood primarily as a technological process bringing together multiple media function within the same devices. Instead, convergence represents a cultural shit as consumers are encouraged to seek out new information and make connections among dispersed media content. [...] The term *participatory culture* contrasts with older notions of passive media spectatorship. Rather than talking about media producers and consumers as occupying separate roles, we might now see them as participants who interact with each other according to a new set of rules that none of us fully understands."[32]

Surveying the diverse body of research into interactive TV, Cesar and Chorianopoulos propose a new way of looking the life cycle of digital content that considers content editing, content sharing and content control as an alternative to the more hierarchical 'produce-deliver-consume' paradigm associated with traditional media[12]. The movement from passive consumers to (inter)active contributors indicates new expectations by users of new media applications. The trend of users' more active engagement in new media technology fits well with the approach of recommendations based on user interaction and our proposal of storytelling as structured recommendation.

The idea of a user of a system taking both roles of consumer and creator is directly reflected in the system setup of wePorter. The idea is that users of the interactive web interface are interacting because they are motivated by a wish to be informed and entertained and at the same time contribute their computational powers in the form of attentional data that helps shape future stories, both for themselves and others. This way we could characterise the *task-request cardinality* as many-to-many.

The Death of the Author, the Birth of Collective Creation

The first part of the title above was originally voiced by Roland Barthes in a 1968 essay bearing the phrase as its title, in which he contemplates the role of the author in literary writing[6]. His title 'the death of the author' points to his criticism to the importance that typically gets associated to the author in the analysis of literary work. To Barthes, a text is not "the message of the Author-God", but rather "a multi-dimensional space in which a variety of writings, none of them original, blend and clash. The text is a tissue of quotations drawn from the innumerable centers of culture". Instead of the author, for Barthes, it is the reader where the diverse backgrounds of text become unified. Barthes' criticism is resolute:

> "the birth of the reader must be at the cost of the death of the Author"

In our aim of reconfiguring interesting sub-clips into a new arrangement, the changing role of the author surfaces in a new context. Barthes' thoughts are relevant in two ways. First because he sees an author's work as the reconfiguration of previous works. Second because he assigns the reader (spectator, viewer, listener, etc) the important role of central interpreter. This links to the contextual nature of human perception discussed in section 2.2 as well as the active role a reader takes in the construction of a coherent story. Explicit reconfigurations of video content may be a way to provide users with a basis from which they 'enact' their own interpretation of a story or a depicted event.

Co-authoring by means of reconfiguration or *'remixing'* is common practice in today's vivid content sharing communities [22] and an important factor in these relatively new forms of creation seems to be attribution[42]. Although classically intellectual property licences mostly have a restrictive function (protecting my intellectual property from being exploited), new less restrictive licences also offer a way of attribution in digital content that is derived from external sources. Less restrictive forms of digital content licensing, like Creative Commons (CC), mean that it is now possible for content uploaded by its original creator, to be used under specified conditions in a new piece of work by someone else. This kind of licences has been noted to be an important facilitator of research into Human Computation[40]. They make it possible for works not only to be used and remixed by other individuals, but also to be incorporated in algorithmically constructed reconfigurations of user-generated content.

Different video platforms are currently offering less-restrictive CC licensing as an integrated part of their services. YouTube currently offers the option of choosing a most basic attribution licence and reports 4 million videos licensed this way [11]. The video platform Vimeo[3] focusses on letting video and animation producers share and showcase their original work. The platform has internalized the use of CC from 2010[3] and many of their users licence their videos such that they can be remixed by others. Figure 4.1 shows that a large part of the licences on the Vimeo platform allow derivatives to be made[1].

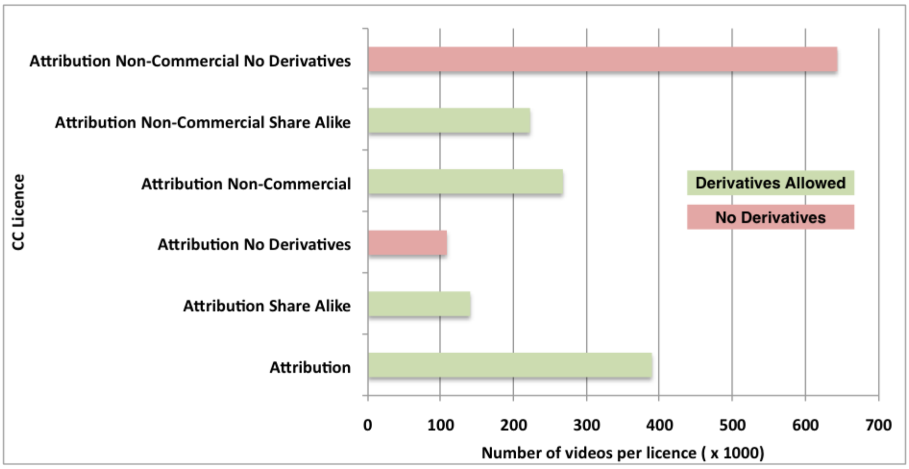


Figure 4.1: Number of videos for each of the Creative Commons licences on Vimeo

Besides the collective actions of the multiple users that help shape the creation of new configurations of content, there is a further level of collaboration between the users and the tools they interact with. Manovich even extends this relation to the tools' designers in his view on collaborative new media authorship:

> "Authoring using [Artificial Life] or [Artificial Intelligence] is the most obvious case of human-software collaboration. The author sets up some general rules but s/he has no control over the concrete details of the work these emerge as a result of the interactions of the rules. More generally, we can say that all authorship that uses electronic and computer tools is a collaboration between the author and these tools that make possible certain creative operations and certain ways of thinking while discouraging others. Of course humans have designed these tools, so it would be more precise to say that the author who uses electronic/ software tools engages in a dialog with the software designers [...]."[43]

[3] www.vimeo.com

4.5.2 The Interface

This sections describes the user interface that directs participation of wePorter users towards solving the purpose of distinguishing local intervals of interest within videos. After a conceptual overview of the functioning we include a walkthrough to explain precisely how the interaction takes place.

We hypothesise that users will spend more time attending to parts of content they find interesting than to parts of content they find less interesting. To state the our assumption about the relation between users' attention and interest more formally we adjust the formulation of Xu et al.[68] to address global interest in video segments. For a video segment i we denote the user u_j's attention to it as $focus(i, u_j)$, which is the time the user spends attending to the object. Let i_1 and i_2 be two video segments. Let's assume after they are both presented to and watched by the user u_j, we have $focus(i_1, u_j) > focus(i_2, u_j)$; then it is reasonable to infer that u_j is more interested in i_1 than i_2.

We further hypothesise that for unstructured UGVC, patterns of interest are at some level shared across multiple people. Or, expressed formally, that if focus rates $focus(i_1, u_x)$ are high for a large number of different users u_x we can extrapolate to users u_y that have not yet been presented with segments i_1 and expect that they might find the segment is interesting to them ass well. The assumption is analogous for segments that have received considerable amounts of low focus rates.

To force a users to make an explicit choice between parts of content for which we would like to elicit their preference, we present two pieces of video playing concurrently and force users to attend to one or the other. In order to get an idea of the variation of interest across a video, each *'source video'* v_k is divided into smaller segments called *'video parts'* $\{i_1, ..., i_n\}$, each of which is presented separately in interactions over time. During this 'parallel play' of two video parts we capture the amount of time user u_j focusses on each of the parts i_1 and i_2 resulting in the pair $\{focus(i_1, u_j), focus(i_2, u_j)\}$ and store this for later analysis.

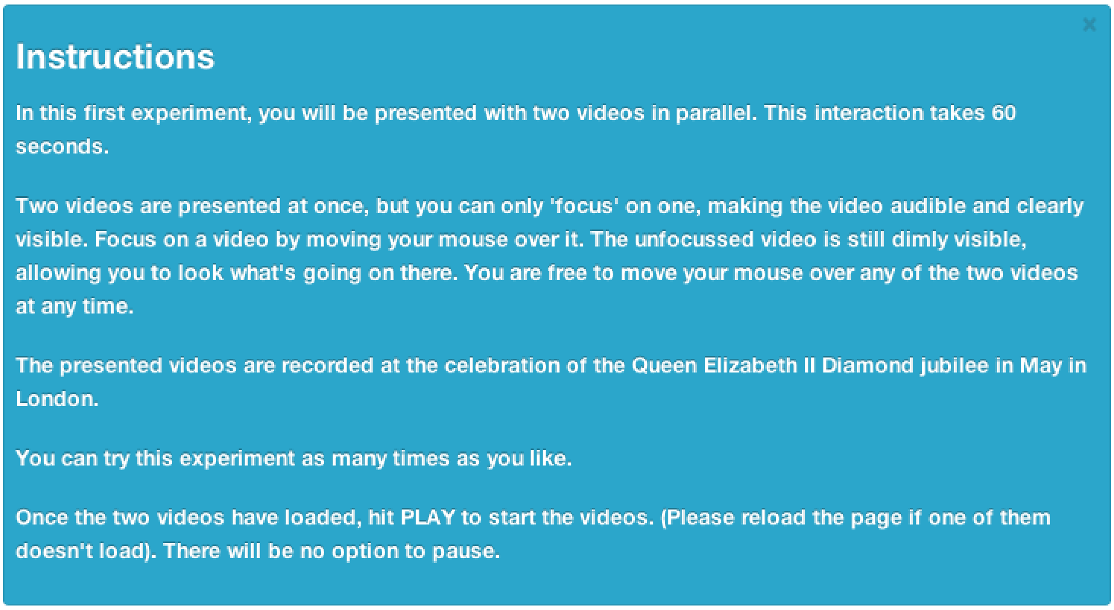
A Walkthrough

When a user opens the wePorter web interface he is welcomed by a short introduction to the project and successively guided to further instructions explaining the experiment. The instructions as they are presented to the user are shown in figure 4.2.

Upon loading the webpage, a database is queried for a pair of sequences made up from different video parts for which the system would like to elicit a user's preference. The two sequences both consist of six video parts that each have a duration of 10 seconds. The interaction of the two sequences playing in parallel thus has a total duration of 60 seconds, reflecting the short time span common across UGVC at YouTube[13, 15]. A detailed description of the algorithm used for the construction of these sequences is given in section 4.6.

After reading the instructions, the user scrolls down to the interactive parallel video player that displays two videos on top of each other. By clicking the 'Play' button, the user starts the interaction and sets in motion the consecutive playback of both sequences in parallel.

During the parallel play of the two sequences of video parts, the user triggers which of the two videos is in 'focus' by placing the mouse cursor over it. When focus is placed on a video, this makes it audible and clearly visible. The unfocussed video is silent and still dimly visible. This partial visibility allows the user to discern to a limited extend what is displayed in the unfocussed video. Seeing something that attracts interest can



Instructions

In this first experiment, you will be presented with two videos in parallel. This interaction takes 60 seconds.

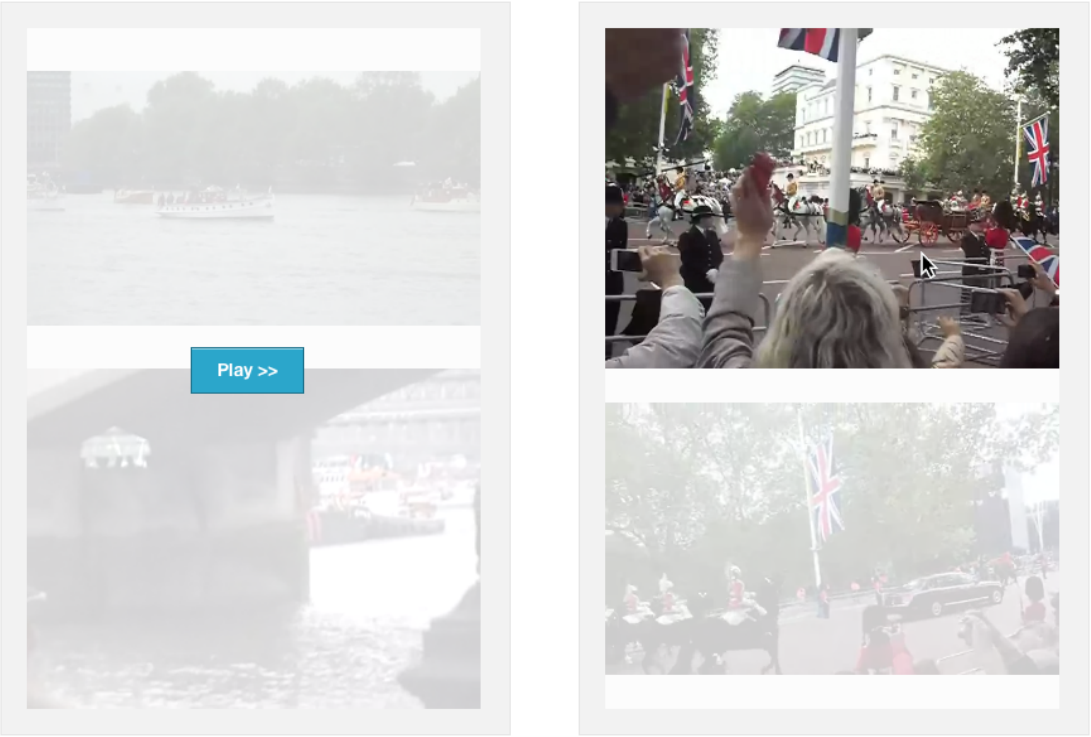
Two videos are presented at once, but you can only 'focus' on one, making the video audible and clearly visible. Focus on a video by moving your mouse over it. The unfocussed video is still dimly visible, allowing you to look what's going on there. You are free to move your mouse over any of the two videos at any time.

The presented videos are recorded at the celebration of the Queen Elizabeth II Diamond jubilee in May in London.

You can try this experiment as many times as you like.

Once the two videos have loaded, hit PLAY to start the videos. (Please reload the page if one of them doesn't load). There will be no option to pause.

Figure 4.2: wePorter Instructions



(a) Upon load

(b) While playing, focus on top video

Figure 4.3: The wePorter parallel play interface

lead the user to change focus from one video to the other. The limitation of only one of the two videos being in focus at once, gives users incentive to explore the narrative space of the parallel sequences. The aspect of focus lets users spread their attention between concurrent parts by:

- making a choice to attend to a video part they find most interesting.
- changing from time to time to check what is being played in the unfocussed video.

We record which video a user is attending to by keeping a count for each of the two video parts playing concurrently and increasing the count for the focussed video every 100 milliseconds. When a video part ends, the count is logged internally on the user's browser side before the next video part is started with its own count. When the parallel sequences are played back completely, the end of the interaction is reached and the counts for each of the 12 video parts are stored in a server-side database. Each pair of counts for two concurrently presented parts, represents a distribution of the user's attention over those parts.

Note that users are never explicitly asked to point at the video that is most interesting. Users are simply instructed as to how the interface works and then left to explore the videos as they like. By recording users' behaviour this way, we achieve a detailed insight into which of a pair of videos a user has attended to at what time. In section 5 we report on the merits of these measures for the processes of filtering and reconfiguration.

4.6 Implementation

This section describes in detail the functionality of the wePorter system, the different components in use and the way they relate to each other. We begin by illustrating how video content is prepared for presentation in the wePorter web interface, and next describe the system framework.

4.6.1 Preparation of Content

In order to get localised feedback on distinct temporal intervals within videos, we present users with a sequence of 'video parts' of equal duration, each originating from their own respective 'source video'. A initial step is thus to prepare video parts so they can be presented in a user interaction. What is played back to a user is a part of the source video referenced by hyperlinks to start and end points. This hyperlinked implementation means slicing up source videos does not involve cutting up video content or recompilation of any sort.

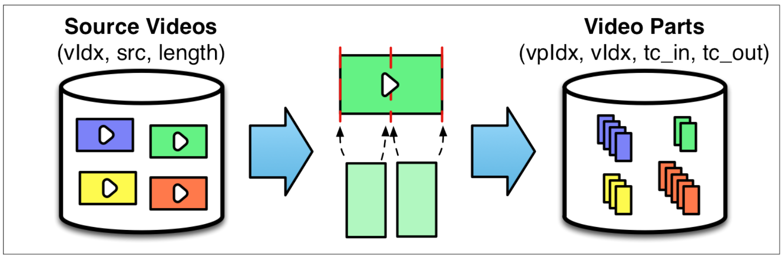


Figure 4.4: Slicing Source Videos into Video Parts by Reference

The wePorter system takes as a starting point a set of topically related source videos, representing a result set that could be acquired by querying a large UGCV platform for video from a large scale public event. We keep a database of source videos, storing their source path and length:

$$video = (vIdx, srcPath, length) \tag{4.1}$$

where $vIdx$ is the video's index. Next, we define video parts as tuples of source video and two time codes referencing start and end:

$$videoPart = (vpIdx, vIdx, tc_{in}, tc_{out}) \tag{4.2}$$

where tc_{in} references the time code within the video indexed by $vIdx$ that is the start of $videoPart$ and tc_{out} references the time code within the video indexed by $vIdx$ that is the end of $videoPart$.

Algorithm 1 shows the procedure to generate video parts from source videos. The algorithm starts at the beginning of a video and extracts a video part for every consecutive window of duration d.

There might be an interval with a duration less than d at the end of a source video that is not included in the resulting set of video parts. Because the parallel sequence player expects video parts of equal length, these end bits are discarded and will not be presented during user interaction. Our assumption is that because of the raw, unedited nature of the videos used in wePorter, disregarding the final few seconds of videos will be tolerable. People recording video in a point and shoot fashion usually stop recording when a phenomenon that prompted them to start filming has ended and so the final bit of their videos does not commonly contain the most important content.

Algorithm 1 Generate Video Parts

```
procedure PARTITION($sourceVideos, d$) ▷ partition videos into parts with duration $d$
    $i \leftarrow 1$
    for all $video \in sourceVideos$ do
        $tc_{in} \leftarrow 0$
        while $tc_{in} \leq video.length - d$ do
            $tc_{out} \leftarrow tc_{in} + d$
            $videoPart_i \leftarrow (video.src, tc_{in}, tc_{out})$
            $tc_{in} \leftarrow tc_{in} + d$
            $i \leftarrow i + 1$
        end while
    end for
end procedure
```

4.6.2 System Framework

Figure 4.5 shows the data framework of the wePorter system. The system runs as a web interface and is accessible online for multiple users at the same time. The server-side functionality is implemented in PHP making use of connections to a mySQL database. On the client-side, Javascript deals with the playback of video sequences as well as keeping track of all interaction data. Upon a user's navigation to the wePorter web page, two sequences are loaded in the parallel video player. A user triggers the interaction by clicking a play button. During the interaction, Javascript running in the user's browser keeps track of the accumulating attentional ratings per video part. Once an interaction has finished, all interaction data is added to the database on the server. The updated interaction data and counts of video parts are subsequently used in the generation of sequences for new interactions either by the same user or a new visitor.

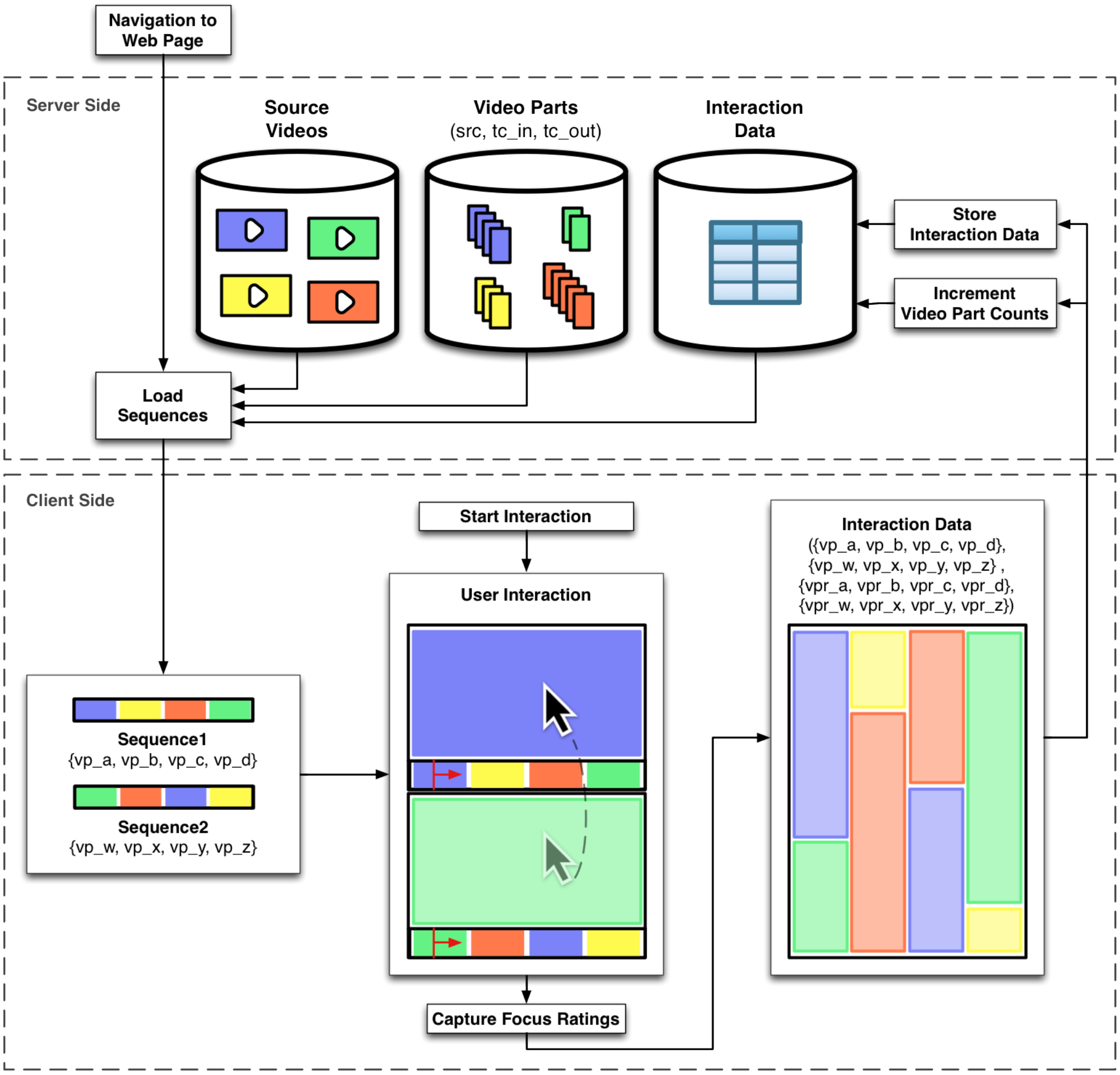


Figure 4.5: System Framework of wePorter

For experimentation purposes, the current implementation maintains a single set of topically related source videos representing the context of ‘encapsulated wander’ for a single query. An extension of the system would be to let users query a live database like YouTube for content of their interest and thus define a dynamic collection of content to explore. Another option would be to give users a choice of which set of videos they would like to interact with. These methods could prove to be useful as they let users interact with content they have chosen themselves, which might make their interaction more interest-driven. In our current implementation, we have chosen to use a fixed set of video content for more controllable experimentation, and left these extensions for future work.

Loading Sequences

The procedure of loading two sequences for a user interactions is detailed in algorithm 2. Given the set of video parts, we iteratively construct two sequences of *n_parts* video parts to be played in parallel. The sequences have equal length and satisfy the following constraints:

1. **Horizontal source constraint:** Video parts within a sequence all originate from different source videos.
2. **Vertical source constraint:** Two video parts that are played concurrently one above the other, originate from different source videos.

These constraints guarantee variety in the interaction, both within a single sequence and across sequences for concurrent parts. On one hand it enables a more varied editing of the video story, which is desired for the user experience. On the other hand it makes sure that each interaction elicits user preference for a variety of sources, which leads to diversified data acquisition.

Amongst the interaction data that is stored in the database, we keep a count for every video part of how many times it has been presented. The counts are used to select from the set of video parts that satisfy the constraints, the ones that are least presented so far. This ensures that all video parts will be presented roughly an equal number of times.

After the two sequences have reached the desired size of *n_parts*, they are randomly shuffled to make sure video parts are presented at different positions in sequence roughly equal amounts of time. Shuffling happens in unison which means correspondence is kept across both sequences so that the constraints still hold. The process of shuffling in unison is described in pseudo code in algorithm 3.

4.6.3 Hypervideo in a Web Browser

Playing back parts of different online videos in a single video experience is a common feature of any video editing system, but this functionality has only recently become available to code that runs in a web browser. Today most videos that live on the web are much like black boxes and this is not just because computers are having a hard time understanding the visuals. When we interact with video online it is almost always on the aggregate level of the entire video. Whether it's playing, sharing, commenting on or linking to video, we lack the functionality of referring to parts that lie within or interact with components like (sub)titles, images or audio as separate entities.

Luckily this is starting to change. An important player in the movement of treating video like the web by hyperlinking, cross referencing and remixing it in code, is Mozilla, whose foundation runs 'Popcorn' [4], a project that aims to make video work much like the web. Part of the Popcorn project is 'Popcorn.js' [5], a Javascript library that intends to open up videos to the web, give it back it's depth and make them more 'soft' and reconfigurable. The wePorter system relies for a big part on the 'Popcorn.js' library for the playback of video parts in sequence.

[4] http://mozillapopcorn.org/

[5] http://popcornjs.org/

Algorithm 2 Load Sequences Random Shuffled

```
procedure LOAD SEQUENCES($n\_parts, videoParts, vpCounts$)
    $seq_1 \leftarrow []$
    $seq_2 \leftarrow []$
    for $i \leftarrow 0, n\_parts$ do
        $selectionH_1 \leftarrow []$          ▷ keep selections of parts that satisfy constraints
        $selectionH_2 \leftarrow []$
        for all $vp \in videoParts$ do                              ▷ Horizontal constraint
            if $vp.vIdx \neq part.vIdx$ for all $part \in seq_1$ then
                add $vp$ to $selectionH_1$
            end if
            if $vp.vIdx \neq part.vIdx$ for all $part \in seq_2$ then
                add $vp$ to $selectionH_2$
            end if
        end for
                                                                                ▷ For $seq_1$:
        $minSelection_1 \leftarrow []$   ▷ select from $selectionH_1$ parts that have minimal count
        $minCount_1 \leftarrow min(count)$ from $selectionH_1$      ▷ look up counts in $vpCounts$
        for all $vp \in selection_1$ do
            if $vp.count = minCount_1$ then
                add $vp$ to $minSelection_1$
            end if
        end for
        $selected_1 \leftarrow$ random from $minSelection_1$
        append $selected_1$ to $seq1$                            ▷ add video part to $seq_1$
                                                                                ▷ For $seq_2$:
        $selectionV = []$
        for all $vp \in selection_2$ do                               ▷ Vertical constraint
            if $vp.src \neq selected_1.src$ then
                add $vp$ to $selectionV$
            end if
        end for
        $minSelection_2 \leftarrow []$    ▷ select from $selectionV$ parts that have minimal count
        $minCount_2 \leftarrow min(count)$ from $selectionV$       ▷ look up counts in $vpCounts$
        for all $vp \in selection_2$ do
            if $vp.count = minCount_2$ then
                add $vp$ to $minSelection_2$
            end if
        end for
        $selected_2 \leftarrow$ random from $minSelection_2$
        append $selected_2$ to $seq2$                            ▷ add video part to $seq_2$
    end for
    $shuffle\_in\_unison(seq_1, seq_1)$
    return $(seq_1, seq_2)$
end procedure
```

Algorithm 3 Shuffle Sequences in Unison

```
procedure SHUFFLE IN UNISON($seq_1, seq_2$)
    $seed \leftarrow make\_seed()$    ▷ to seed $random\_generator$ twice identically
    $random\_generator.set\_seed(seed)$    ▷ set seed
    $random\_generator.shuffle(seq_1)$    ▷ shuffle
    $random\_generator.set\_seed(seed)$    ▷ set seed
    $random\_generator.shuffle(seq_2)$    ▷ shuffle
    return $(seq_1, seq_2)$
end procedure
```

Chapter 5

Evaluation

5.1 Introduction

This chapter reports on a number of experiments on the wePorter system. We report on the feedback that is received from users' interaction through the use of the wePorter web interface. We show how this data can be used for the purposes of filtering segments within a video and the reconfiguration of these segments into a new video story. We present results from a user evaluation study on the merit of filtered and reconfigured content and also include results obtained from a user questionnaire supplied along with our main experiment.

5.2 Preliminary Experiments

5.2.1 Positional Bias

Positioning two video's one on top of the other, might inflict a bias for users in their attentional behaviour. It might be the case that videos on the top are systematically more attended to than videos displayed below. We've experimented to see whether such positioning bias effects occur.

To see whether the positioning of a video has effect on users' attentional behaviour, we've presented two groups of users the same two videos playing in parallel and varied their relative positioning. In two trials, participants were divided by random into control group and test group. The first trial was conducted with 37 participants (24 control, 13 test), the second with 32 (18 control, 14 test). In each trial, test group participants were show the same two videos as the control group, but their positioning was flipped. Figure 5.1 shows a visual explanation of the experimental setup.

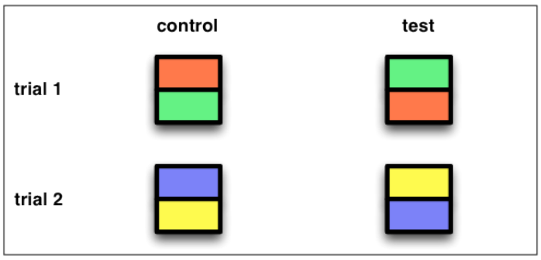


Figure 5.1: Setup for Positional Bias Experiment

5.2.2 Context Dependency

We propose a statistical analysis of interaction data to inform the reconfiguration of initially unstructured video parts. We hypothesise that:

1. Users' attentional behaviour depends on the sequential ordering of video parts
2. Data about users' attentional behaviour can indicate what are preferred orderings.

Before we investigate the second hypothesis in section 5.3, we must scrutinise the first. In order to test whether users' attentional behaviour is dependent on the sequential ordering of video parts we have run a experiment in two trials. The first of these had 35 participants, the second 28. In each trial participants were presented with with a two sequences of three video parts playing back continuously using the parallel video player described in section 4.5.2. Based on random picks, roughly half of the participants were labelled as control group the others as test group. Participants in this group where shown two sequences where all video parts originated from different sources. This was changed for the second group, where participant were shown parts across the sequences that clearly belong to the same source video.

The first trial presented test group users with a first part in the bottom sequence that was followed by a part from the same source video as the third part in the top video. The second trial presented test group users with pieces from the same source video in the first and third part of the top sequence and second part of the bottom sequence. The baseline sequences shown to control group participants had video parts of different sources on all positions and had final parts of both sequences identical to test group users. A visual description of these conditions is shown in figure 5.2. Where we use the same conventions to display sequences, video parts and colouring to indicate source videos as in figure 4.5.

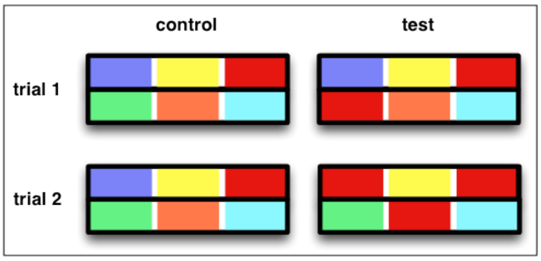


Figure 5.2: Setup for Context Dependency Experiment

The effects of Positional Bias and Context Dependency are mainly interesting when experiments involve large amounts of data. This is first of all because of the increased statistical power that large data set bring to the table for these experiments themselves. Second, the experiments, in particular the one studying influences of context, are aimed at acquisition of knowledge that helps to steer the design of methods that needs many more data points that the limited set we have been able to acquire in our main experiment. Initial sets of data for both the Positional Bias and Context Dependency experiment have been obtained, but as they do little for the purpose of the current thesis, their analyses is left out of this work. The descriptions of the two experiments are included to indicate the two issues at hand and point to possible ways to investigate.

Id	File Name	Title	Length (sec)	Views
1	“jubilee_01.webm”	“Diamond Jubilee London 5th June 2012 The Mall Video 3”	186	45
2	“jubilee_02.webm”	“Diamond jubilee London 5th June 2012 The Mall”	47	108
3	“jubilee_03.webm”	“London Thames - Queens Diamond Jubilee Pageant - Dunkirk Little Ships, June 2012”	234	2304
4	“jubilee_04.webm”	“My Diamond Jubilee video!”	54	28
5	“jubilee_05.webm”	“Queens Barge. Diamond Jubilee London 2012 VIDEO Ursula Maxwell-Lewis 0053”	163	88
6	“jubilee_06.webm”	“Queens diamond jubilee London 5th June 2012”	30	43
7	“jubilee_07.webm”	“Queens Diamond Jubilee Procession, 5th June 2012, London, UK”	133	58
8	“jubilee_08.webm”	“Queens Elizabeth 60th Diamond Jubilee London 2012. 1st”	73	203
9	“jubilee_09.webm”	“Queens Elizabeth 60th Diamond Jubilee London 2012. 2nd”	165	246
10	“jubilee_11.webm”	“Queens Elizabeth 60th Diamond Jubilee London 2012. 14th”	390	88

Table 5.1: Source Videos used for the main experiments (Views count accessed on 23-09-2012)

5.3 Main Experiments

Our main experiments use the system framework described in section 4.6 for the preparation and presentation of video content, data capture from user interaction and storage of interaction data. The experiments we report on here are based on the interactions from a total of 51 persons who all participated once over a period of a week.

5.3.1 Setup

For our main experiments we use a set of 10 unedited, user-generated videos returned in response to the query “Diamond Jubilee London” on YouTube. The videos along with their title, length and view count at time of retrieval is shown in table 5.1. As mentioned in section 4.6, we divide source videos into video parts of equal length and generate two sequences consisting of an equal number of video parts to present in parallel. Partitioning the source videos from table 5.1 yields 142 separate video parts.

The sequence loading procedure shown in algorithm 2, prepares two parallel sequences consisting of six video parts each. Each interaction thus presents a user with twelve video parts. For the 51 interactions focus rates are captured. Video parts have each been presented between 3 and 7 times.

5.3.2 Parallel Play Interaction Data

Clean Data

Data returned from the capturing of attentional behaviour in the parallel player interface might have several deficiencies that we deal with by preprocessing the data before we start analysis. Deficiencies range from artefacts induced by the inaccurate functioning of the interface to users' behaviour patterns that make their data less revealing. Such patterns are expected to be caused by misunderstood instructions and minor technical shortcomings in the implementation of the web interface.

Some entries show focus rates of both sequences consistently valued at zero. This can either be caused by a malfunction of the focus counter functionality or by a user simply not focussing on either of the videos. These entries are completely deleted from the dataset. Although not present in the data required in our current experiments, focus rates of segments within a single sequence might also be consistently high valued. This indicates behaviour of someone who decided not to change focus. Although it might be a sign that the user is simply most interested in the one particular sequence, we would also discard these entries as they are most likely to result of a lazy participant who decided not to move the mouse or someone who misunderstood the instructions. Moreover, interactions patterns that aren't the cause of active exploration of the content are not likely to reveal useful information with regard to a user's interest.

The unit of measurement for focus time as captured by the parallel play interface is 100ms. A ten second clip can theoretically thus acquire a focus rate of 100, indicating a user has focussed for the complete duration of 10-seconds. A user dividing focus over two parallel videos would result in two focus rate around 50 that together add up to maximally 100. Practically however, many focus pairs in the dataset have a combined sum over 100. This is most likely cause by the method of logging focus counts. Although counters are only increased when a video is playing to prevent a video's potential load time to contribute to its focus rate, there may still be glitches induces by videos not playing bad continuously in the web browser. Also, moving the mouse quickly back and forth between the two videos can cause the two counters to be increased during a single time frame of 100 ms. These technical shortcomings should be addressed in a future implementation.

Because of the varying sum of focus rate pairs, it is more indicative to look at the ratio between the two parallel rates than to absolute rates. This way a focus rate of 50 in pair $\{focus(50, u_j), focus(50, u_j)\}$ has a different contribution than in pair $\{focus(50, u_k), focus(0, u_k)\}$. Likewise, it ensures that a rate of 30 in the pair $\{focus(30, u_l), focus(30, u_l)\}$ has a contribution equal to that of the rate of 50 in the pair received from user u_j.

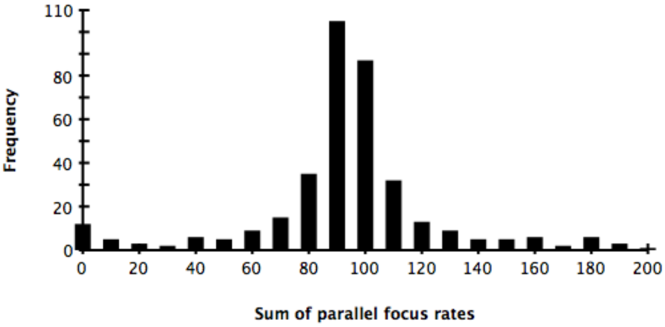


Figure 5.3: Occurrence of different sums of parallel focus rates

A further processing step is to weigh the ratios depending on the size of their sum.

This is to emphasise focus pairs with a sum around 100 as this indicates a user has spend the full playing time focussing on at least on of the presented sequences. figure 5.3 shows the distribution of the sum of parallel focus counts. Focus pairs whose rates sum to values between 20 and 160 are weighted once, sums between 70 and 120 are weighted twice. Focus rates that sum to other values are discarded.

Figure 5.4 shows both average absolute focus rates and average weighted ratios received for all video parts. For clarity, ratios in the plot are scaled by a factor 100 to match the absolute rates' order of magnitude.

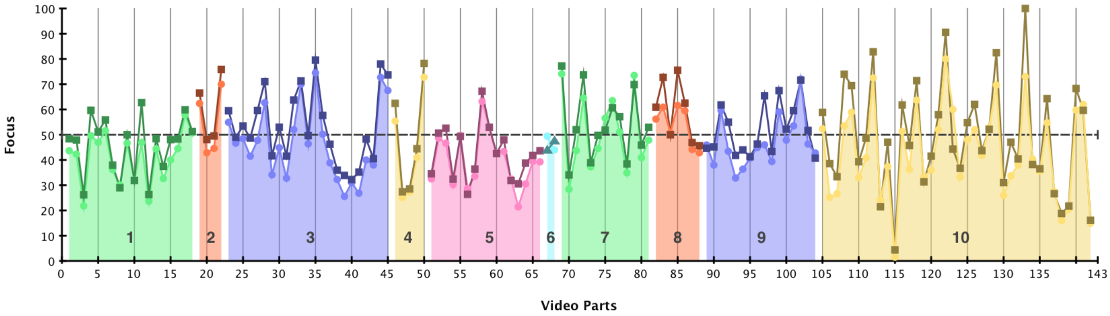


Figure 5.4: Average focus rates and weighted focus ratios for individual video parts

5.3.3 Attention-based filtering

Considering the assumption that user interest may be inferred from many users' focus data across different interactions, we can look at the focus data and use it to form a selections of *best* and *worst* attended-to video parts.

To find a reasonable amount of video parts for most of the source videos in the experiment that make it into the *best* and *worst* sets, we consider focus ratings over 60 and below 40 respectively. Selection of parts for filtering out can be straight forward based on a ranking of all video parts within the *worst* set of parts and a rejection of the $x\%$ video parts with the lowest rates. For an optimal selection for reconfiguration, a slightly more complex procedure may be preferred, as simply selecting the top $y\%$ of the *best* set may result in several video parts from the same source video. This may not be desired for reconfiguration and in that case diversity in source videos should be promoted in the selection procedure.

5.3.4 Evaluating Focus

By capturing the amount of focus time, we receive measures for user attention. We hypothesise that these measures for attention help point to patterns in user preference. If the two dimensions turn out to be linked, it makes sense to base segmentation (and subsequent reconfiguration) of potentially interesting parts of video on the focus data captured in our parallel play interface.

To see how focus measures relate to user preference, we compare video parts which have received low focus rates to those who received relatively high rates. We construct three types of videos from our data set of video parts based on their weighted focus:

1. two complete sets of *parallel play sequence pairs*, one consisting of two sequences of 6 parts from the *best* set, the other consisting of two sequence of 6 from the worst set.

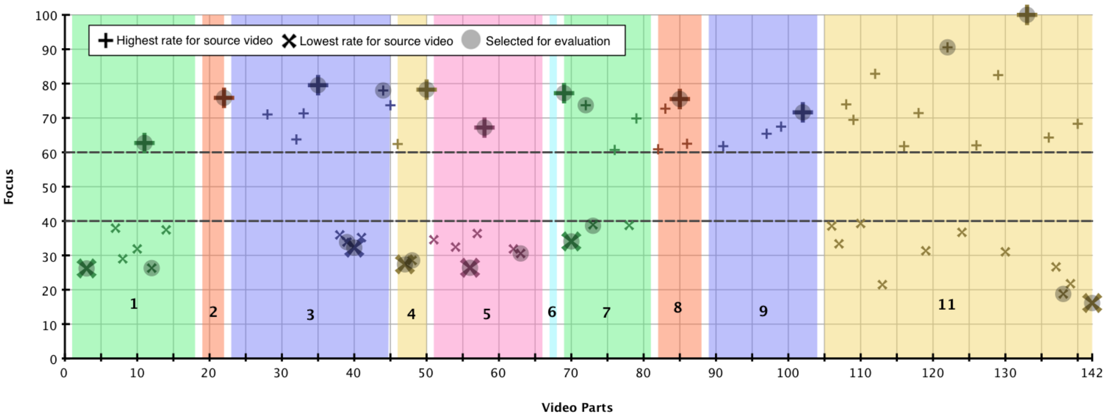


Figure 5.5: Video parts considered for filtering based on their focus ratios

For both sets, video parts with the highest (and lowest respectively) focus rates per source video are selected to encourage variety across sources in the reconfiguration.

2. four *sequences of 6 video parts*, two consisting of the video parts with the highest (lowest) focus rate per source video, two consisting of the 6 video parts with highest (lowest) focus rate that were not yet selected for the parallel play sequences.

3. twelve *single 10-second video parts*, forming 6 pairs of corresponding video parts with minimum and maximum focus rate for their mutual source video.

Subjects in the evaluation experiment were presented with pairs of content of the three different types described above, one video from the *best* set, the second video from the *worst* set, without subjects knowing the nature of the videos' content. The positioning left or right on screen was done at random to counter possible effects of bias by the positioning.

After the presentation of the two videos, subjects were asked to rate what they were shown based on how *informative*, *entertaining* and *interesting* they thought the content was. Subjects were instructed to rate content on a range form 1 being very {uninformative, unentertaining, uninteresting}, 3 being neutral, 5 being very {informative, entertaining, interesting}.

Besides this, they were asked to choose which of the two presented videos has their preference. Histograms of the received rating are include per video type for each category of assessment below.

Parallel Play Interaction

Ratings For each of the three dimensions (indicated by colour) of a user's assessment of a parallel played sequence interaction we have plotted how the frequency of the occurrence of the distinct ratings differs for sequences sourced from the selection of video parts with either high focus rates (the best set) or low focus rates (the worst set).

If our hypotheses on the relation between focus and interest are correct, we would expect higher evaluation ratings for the parts that are sourced from the best set, compared to those from the worst set. On the level of parallel sequence interaction this is the case for both entertainment ratings and interest ratings. On these two dimensions, videos from the worst set are more commonly given low ratings, while videos from the best set are more prominent on the high end of the rating spectrum. This is indicated by greater frequency of high ratings for the best set and greater frequency of low ratings for the worst set.

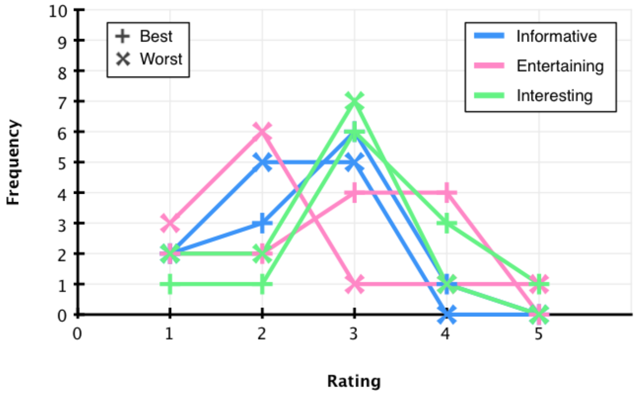


Figure 5.6: Histogram of ratings for parallel player sequences

Preference Looking at users' choices for preference does not reveal a very insightful pattern. Although the downward first segment of the line in figure 5.7 indicates a collective preference of the interaction featuring content from the best set, the difference is extremely small so not very significant. Because of the small number of subjects it is hard to find telling results. Results that show more extremely difference between the two sets of content are of most relevance.

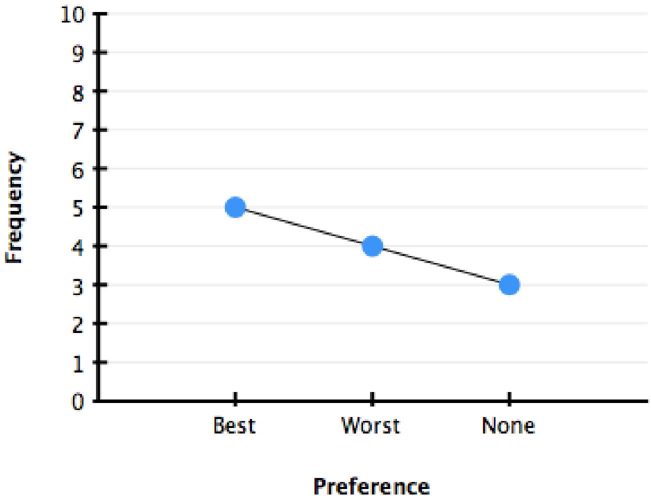
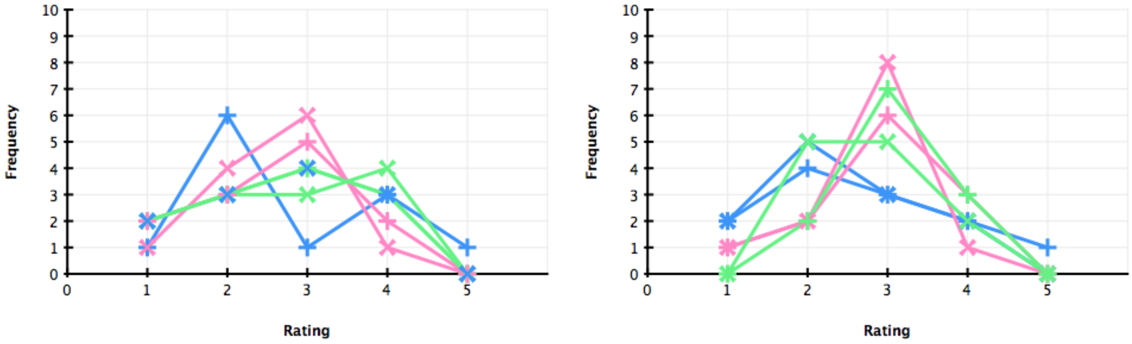


Figure 5.7: Histogram of preferences for parallel sequences

Sequences

Ratings Of the two sequences we evaluated, the second shows the most indicative configuration of ratings for the dimension of interest. Although not very accentuated we see the same pattern of best set content receiving more high-end ratings and worst set content receiving more low end ratings, with their lines cutting in the middle.

Preference The leaning to 'good' content for the second pair of sequences is more clearly accentuated by the choices of preference. Figure 5.9 points to a larger difference between



(a) Sequence 1

(b) Sequence 2

Figure 5.8: Histogram of ratings for two evaluated sequences

the number of people choosing the different sets in favour of the content with high focus rates.

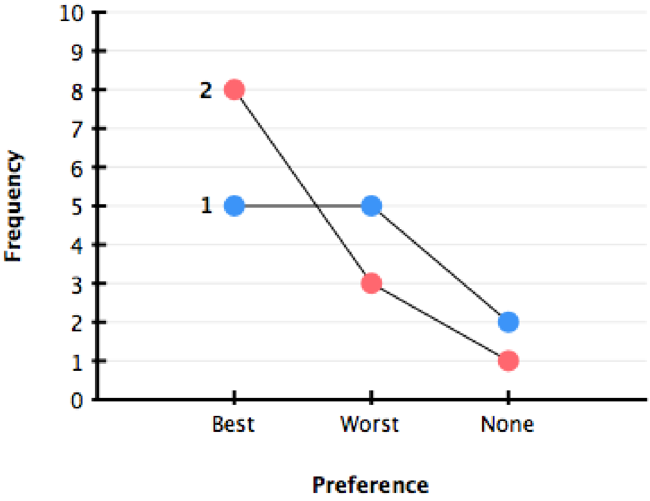
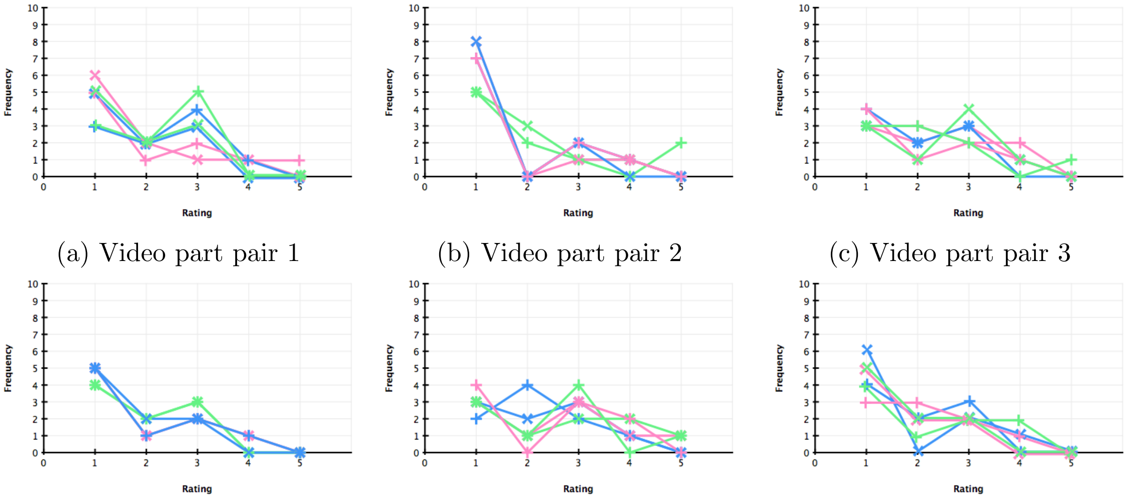


Figure 5.9: Histogram of preferences for one minute sequences

Video Parts

Ratings Looking at the ratings of the 10-second different videos parts, two videos are most interesting. Video pair 1 and 6 show the most difference in ratings between the two sets of content. Manual inspection of the video parts (originally numbered 11 and 3 in figure 5.4 for pair 1 and 133 and 142 for pair 6) reveal that both video pairs consist of two pieces of content with a significant difference in activity. Because of the unedited nature of the content used for the experiment, the scene settings are mostly the same. Yet in one of videos (pair 1) originating from the set with high focus ratios, a carriage transporting her majesty Queen Elizabeth passes by in full view and in pair 6 the video from this set shows a zoomed-in shot of a particular boat. The alternative video parts (from the set with low focus ratios) respectively show a couple of horses together with a handful of union jacks and a zoomed out pan-shot capturing many people filming and photographing the Jubilee's boat parade on the river Thames. Video parts in pair three have a similar nature to those in pair 1, but do not show similar patterns in evaluations. The content in



(a) Video part pair 1

(b) Video part pair 2

(c) Video part pair 3

(d) Video part pair 4

(e) Video part pair 5

(f) Video part pair 6

Figure 5.10: Histograms of ratings for six 10-second video parts

the other pairs differs hardly.

Preference The plot of preference frequencies in figure 5.11 shows an almost unanimous choice for the parts from the best set for pairs 1 and 6. This is a nice result, as it indicates that the distinction by our attentional filtering mechanism corresponds to evaluation of preference for two pair that show a significant difference in contents. While pair three has a similar difference in content between the two videos, subjects show no collective preference for the video from the best set. Overall best set videos have received 38 preferences, while worst set have been preferred only 22 times (32 times no preference was given). While this doesn't indicate a unanimous agreement, it does show correlation between the distinctions made by the attentional filtering and user evaluation. As can be expected the effects are strongest for video parts that differ in content.

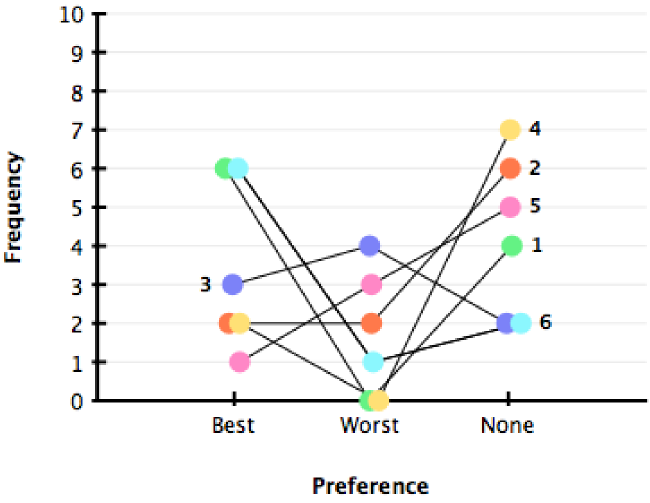


Figure 5.11: Histogram of preference for 10-second video parts

5.4 Questionnaire

In addition to the interactive experiment using the parallel play interface subject were presented with a questionnaire asking them about their use of online video and evaluation of the interface. The questionnaire also gave room to express general comments about the experiment. A copy of the questionnaire as presented to the users is included in appendix A.

5.4.1 Questions

Online Video Content

To get a better picture of the subjects who participated in the experiment, they were instructed to rate on a discrete scale from one to five the frequency and aggregate daily duration of their interactions with online video as well as how often they feel the content they view is news-related. Figure 5.12 shows amongst others that a large majority of the subjects is accustomed to watching online video on a daily basis, typically for a durations between 10 and 30 minutes.

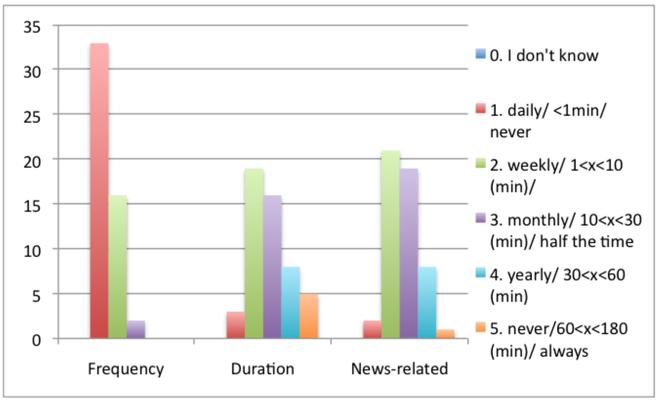


Figure 5.12: Questionnaire Results for questions relating to online video consumption

We also asked the users about their own engagement with online video. Figure 5.13 shows that the group of subjects in our experiment include both active and non-active individuals.

The wePorter Interface

Subjects seem to slant slightly to a positive evaluation of the interface, but opinions vary. Subjects are also ambivalent about the idea of seeing their own recorded video back in an algorithmic reconfiguration as the one presented in the experiment.

5.4.2 Feedback from Comments

> “[...]the technology may [...] have many uses like the crowd sourcing of video editing or the training of AI to mimic human audio visual focus and attention”
> - Mia

As part of the user feedback form, participants were also given the option to leave their comments. Thinking of the potential of the interface, some comments, like the one above,

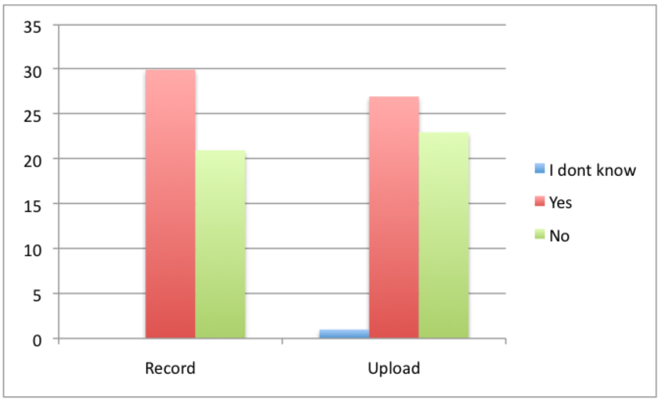


Figure 5.13: Questionnaire Results for questions relating to user engagement with online video

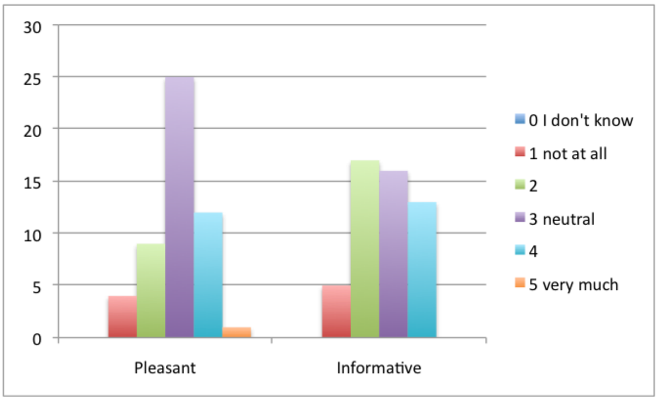


Figure 5.14: Questionnaire Results for questions relating to the wePorter interaction

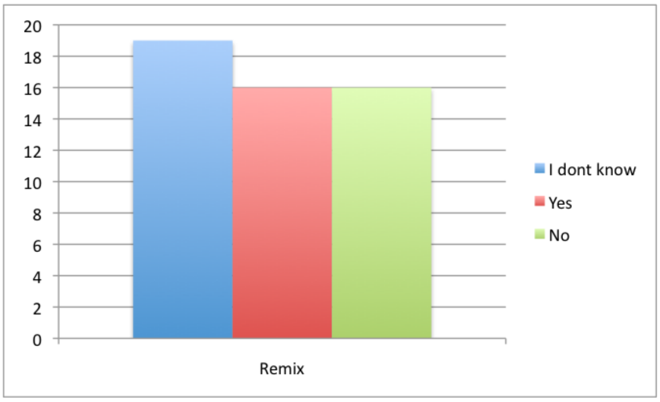


Figure 5.15: Questionnaire Results for the question “Would you like to see your own video content remixed in such a way?”

hit the nail right on the head. Others touched upon different aspects of the experiment, the interface and the content of the videos. Overall a number of salient points emerged from the comments:

- **"I would like to see news this way"** - People were positive about the way video was presented in parallel and were enthusiastic about the possibility to interact.
- **"I believe there was a bug"** - A number of people reported difficulties in the playback of videos. Most issues concerned one or more video parts not immediately playing after the preceding one had finished. Besides causing data to be less clean, this caused some users to be confused.
- **"The subject and content of the videos was uninteresting"** - Many people said they were not particularly interested in the topic of the presented videos. This meant that often they weren't drawn strongly to a particular video and did not feel a strong reason to shift focus from one or another.

Some participants even offered ideas as to how they saw the project could be extended:

> "Idea is great and project full of potential, in particular for big events which are well covered and allow multi-angle views of an action. It would be interesting to have information about the content producer displayed discretely on the player. That way the audience could vote on the quality of a source, and in time reward the owner for it's content, encouraging him to submit more videos in this system." - Marc

5.5 Discussion

It is first of all interesting to see which parts of the initial sources videos are picked up by the attention-based filtering mechanism. Manual inspection shows that for source videos that feature intervals of prominent visual activity, parts of this concept can be automatically selected and used in reconfiguration. The low number of interactions per video part definitely contributes to the variation in focus data over time. Increasing the number of interactions per video part will smooth out the data and solidify mountains of attention and valleys of lack of attention.

The initial evaluation performed at multiple levels of reconfigured or deconstructed video, shows that although user evaluations and preferences differ considerably across much of the content, some footage shows signs of correspondence between the time spent focussing by several users on segments of video and the collective evaluation of these parts. Moreover, the global correlation between acquired focus rates and the user preference data acquired in the evaluation experiment, indicate that we are on to something. For six out of the nine pairs of reconfigurations, the 'filtered in' piece of content selected for its high focus rates, is evaluated by a majority of the evaluation subjects as most preferential. This is compared to one pair of 10-second video parts where the 'filtered out' member received a majority of the preferences.

Chapter 6

Discussion and Future Directions

This chapter briefly reviews the approaches taken in this work and then points to several ideas that are may provide the basis of viable extensions to the presented work.

First of all there are several remarks to be made about the experimental setup as presented in the previous chapter. The experiments executed to test the viability of the methods used in the wePorter system, suffer from a pivotal shortcoming in their design. Although 51 subjects is represents a reasonable amount of participants, the large amount of separate video segments causes each part to be interacted with only a handful of times in the current experimental setup. Although a case can be made that a scale-up is within reach considering the vast amount of user interactions received by online video platforms nowadays, it would have been wise to focus on a smaller set of content in order to acquire more telling data for each point.

Notwithstanding this issue that may be tough of as limiting to the results, it is actually very insightful to look at the results from the limited interaction data. Not only do the proposed filtering methods pick up salient segments in larger source videos, the selected shots are also evaluated as relatively preferable over shots that would be filtered out due to low focus rates. These quick results after a small number of interactions of human computers, might be attributed to the nature of the raw, unedited user-generated video content used in the experiment. By aggregating focus data over all users collectively, we might be able to filter an a high level between parts of content that are ‘exciting to watch’ and ‘not worth my time’. The validity of these ideas should of course be tested in future work.

Besides the extension of acquiring more user contributed data per video segment, another lead that would be very interesting to follow is iterative application of filtering methods, possibly to eventually leading to a convergence to a meaningful reconfiguration of the most salient content.

The videos used for the main experiments have a total length of 25 minutes and their individual view counts range from 28 to 2304. Using the length of individual videos and the number of times they have been viewed, we have calculated that the total time spent on watching the 10 videos above, amounts to over 185 hours. That is a lot of user interaction that could help in the computation of the most interesting video segments. If directed through our one minute parallel play interface, all this user interaction would result in more than 11000 complete interactions. With 12 video parts presented in each interaction, it would amount to more than 130000 attentional ratings for video parts or over 900 ratings per part.

This is not yet regarding the system’s filtering functionality. Once reliable estimates of user interest have been established from the collection of captured attentional ratings, we can filter for the parts that seem most interesting, that way enabling a convergence towards the most interesting video segments. A simple way of doing this would be to rank all video parts according to their average attentional rating and discard the parts that are systematically less attended to, on the assumption that they are considered less interesting. More complex procedures are of course possible, for example taking into account the number of ratings a part has received, the positions in sequence at which parts have been presented or the kind of users that have submitted the interactions (e.g. first time users versus experienced users). Once the initial set of source videos has been filtered, more data can be acquired for the remaining set, after which filtering can be applied again. This iterative process of filtering can continue until the process yields a small subset of video part that have acquired most attention in aggregate.

Filtering video parts to converge to a subset of the source videos that is iteratively narrowed down, means that most interactive computation will be focussed on the video parts that receive most attention. There is an obvious issue of exploration versus exploitation here. When is filtering applied and what part of the current set of content is discarded in an iteration. Related to this filtering is the meaningful reconfiguration of segments into a new assemblage. Data-driven segment reconfiguration is currently left unexplored and it would be very exciting to see it investigated in the future.

Besides conceptual extensions the proposed framework, there are numerous variations possible in the current implementation that would be good to explore. In its current version the system uses aggregate counts for the time a user focussed on a particular sub-clips. Since the interactive player is set up to capture users' focus every duration δ (currently 100 milliseconds), this could also become the resolution of recording. That way each video parts would have $length/\delta$ time bins in a focus histogram. Another variation that will most likely yield exciting experiments, is to increase the number of videos displayed in parallel. Other potential variations include overlapping segment windows, using differently sized segment durations, the use of different video part durations within a single sequence.

Chapter 7

Conclusions

This thesis has aimed to show how different characteristics of digital video make the medium hard to interpret computationally. A main issue in the meaningful computational analysis of video content is the semantic gap between low-level features extracted by computers and high-level semantic interpretations used by humans. We have shown why the gap is hard to close by current methods and have pointed to human computation as a paradigm that may prove particularly helpful in alleviating the problems posed by the semantic gap. Several aspects of the medium video such as the sensory nature of much of the information included in video, make the joint effort of humans and computers an appropriate framework in addressing challenges relating to meaningful interpretation of video content. Furthermore, the current proliferation of online video tools, platforms and networks may provide useful entry points for human computation systems directing human cognitive power to the purpose of solving tasks currently left unsolved by computers.

In our investigation of the use of human computation for meaningful video interpretation, we have implemented our own system called 'wePorter' that uses implicit attentional feedback to provide interest-based video filtering at segment level. We have proposed 'parallel play' as a method for user preference elicitation that may prove particularly useful for time-based multimedia content. The system reconfigures hyperlinked parts of videos into new sequences, used both as unit for data acquisition and unit of presentation of filtered content. The developed framework allows for experimentation with filtering and recommendation based on implicitly acquired attention data.

Although having received only a small number of interactions per video segment, initial evaluation shows that the filtering provided by our system corresponds to collective ratings of interest and more general assessments of preference. We have experimented on the broad domain of raw, unedited user-generated content contributed by attendees of a single large-scale public event. Experiments show that the proposed methods for filtering pick out video segments that are found to be evaluated relatively interesting and preferential compared to segments receiving low scores from our attention based methods.

Chapter 8

Acknowledgements

I would like to thank a number of people who've been instrumental in the development of this thesis as well as my own development along the way.

My supervisor Dr. Marian Ursu for providing focus, support and inspiration by asking the right questions every time again.

Prof. Mark Bishop for leading the programme, guiding us far and wide along different ideas in cognitive science, always with enthusiasm and personal attention.

'her Smallness' Lucia for her never-ending positive support during the structuring of our ideas.

The 'Chicken' of Batavia and its inhabitants for making the place like a second home to me. In particular Louise for keeping me up late with great music from all over the world.

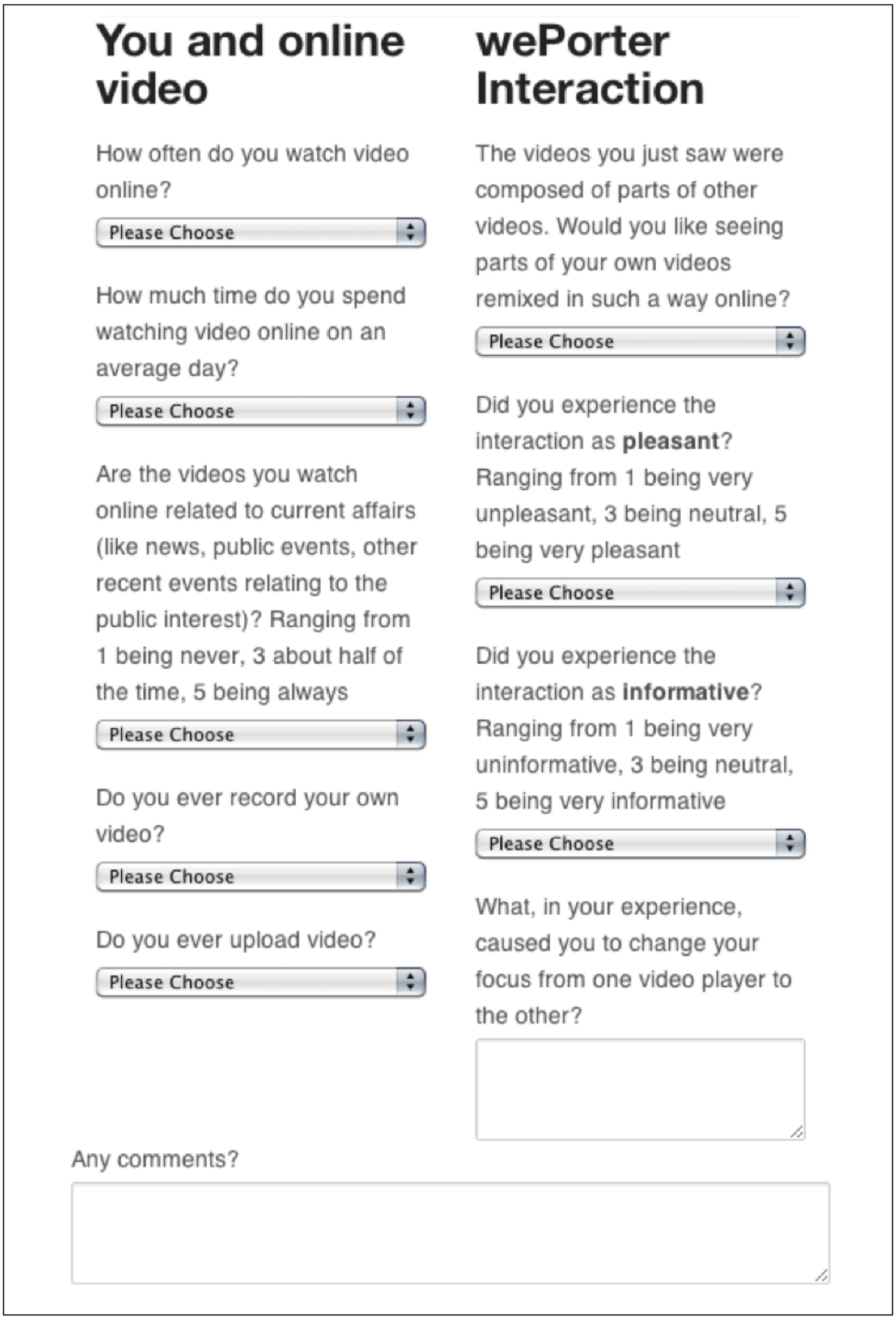
The people together with whom we made 'Picnic' an inclusive, friendly and safe learning and teaching community, for sharing their knowledge and enthusiasm to make things happen.

Simone for being a truly nourishing host and dear partner in life and crime during my stay in beautiful Rennes les Baines, where much foundational work for this research was done.

Jan and Pim for bringing out the best in me, no matter how many kilometres our friendship spans.

My mother and sister for being so super supportive during the final week.

Goldsmiths with her unconventional Department of Computing for having me experience the creative side of Computer Science and letting me merge my passions for AI and video.



You and online video

How often do you watch video online?

Please Choose

How much time do you spend watching video online on an average day?

Please Choose

Are the videos you watch online related to current affairs (like news, public events, other recent events relating to the public interest)? Ranging from 1 being never, 3 about half of the time, 5 being always

Please Choose

Do you ever record your own video?

Please Choose

Do you ever upload video?

Please Choose

wePorter Interaction

The videos you just saw were composed of parts of other videos. Would you like seeing parts of your own videos remixed in such a way online?

Please Choose

Did you experience the interaction as **pleasant**? Ranging from 1 being very unpleasant, 3 being neutral, 5 being very pleasant

Please Choose

Did you experience the interaction as **informative**? Ranging from 1 being very uninformative, 3 being neutral, 5 being very informative

Please Choose

What, in your experience, caused you to change your focus from one video player to the other?

Any comments?

Figure 1: Questionnaire in main experiment

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