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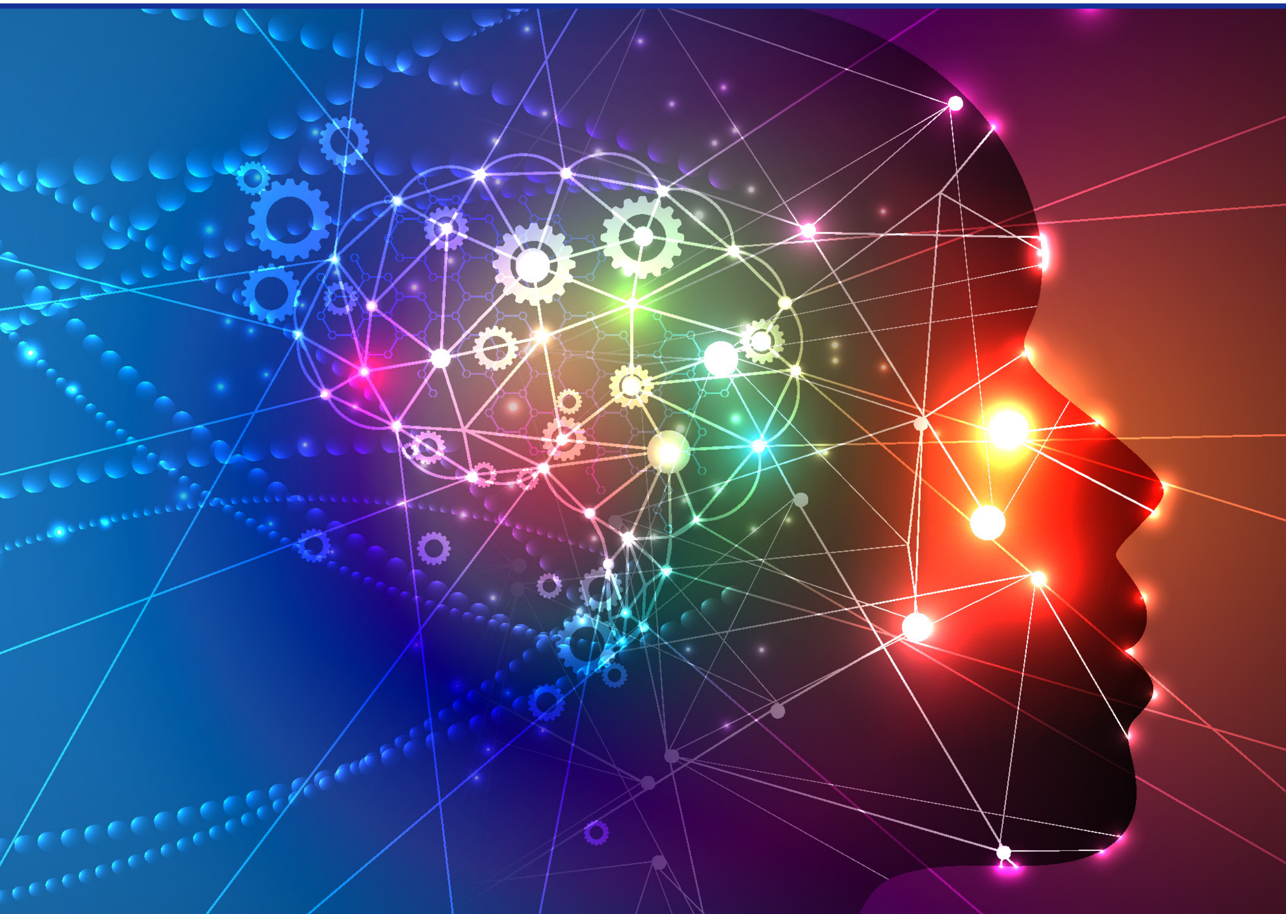
Linda Alksne

VIDEO LECTURES AS CODE ANALYSIS IN THE BLENDED LEARNING MODEL

Summary of the Doctoral Thesis



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Liepāja University
Faculty of Science and Engineering

VIDEO LECTURES AS CODE ANALYSIS IN THE BLENDED LEARNING MODEL

Linda Alksne

SUMMARY OF THE DOCTORAL THESIS
for obtaining a doctoral degree in engineering
in the field of electrical engineering, electronics, information and communication technologies,
in the subsector of e-learning technology and management

Scientific supervisor
Dr. habil. phys. Andris Ozols

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The Thesis consists of Introduction, 3 chapters, 13 sections, 52 subsections, Results, Conclusions, list of used literature sources and appendices. The Thesis includes 57 figures and 19 tables.

Type of work: Thesis in the field of electrical engineering, electronics, information and communications technology in the subsector of e-learning technology and management.

The scientific supervisor of the Thesis: Dr. habil. phys. Andris Ozols, Head of Optics Department of Riga Technical University during the development of the Thesis.

Reviewers of the Thesis:

- Dr. paed. Sarma Cakule, Vidzeme University of Applied Sciences, Latvia
- Dr. Sc. Ing. Jurģis Poriņš, Riga Technical University
- Ph. D. Carlos Turro Ribalta, Valencia Politechnic University, Spain

The defence of the Thesis will take place on 20 March 2023 at Riga Technical University at the open meeting of RTU Promotion Council RTU P-21 “E-learning Technologies and Management” in the field of electrical engineering, electronics, information and communication technologies.

Chairman of the Promotion Council of Riga Technical University Dr. phys. Atis Kapenieks

Secretary of the Promotion Council Mārīte Treijere

DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for the review to Riga Technical University for the promotion to the scientific degree of Doctor of Science (Ph. D.) is my own. I confirm that this Doctoral Thesis had not been submitted to any other university for the promotion to a scientific degree.

Linda Alksne ……………………………. (signature)

Date: ………………………

Annotation

In e-studies, a video lecture is used as one of the basic information transfer methods. In this research, the video lecture is considered as a code by which information is passed on to students. In 1948, C. E. Shannon developed an information theory presenting it in his article "A Mathematical Theory of Communication" in which he discusses the most important aspects of communication systems. Entropy plays a key role in Shannon's information theory. Entropy is a measure of information from a source of information.

The aim of the study was to perform an entropy analysis of video lectures in order to find out the relationship between the type of video lecture and the guidelines that have been proven in the scientific literature as crucial for increasing students' perceptual capacity.

In the course of the research, guidelines for filming easy-to-understand video lectures have been compiled and defined, students' video lecture viewing habits have been studied and 11 different types of video lectures have been selected, for which the average video and audio entropy has been determined with the help of Matlab. The obtained results are analysed by studying the effect of the guidelines on entropy, as well as the dependence of entropy on the chosen way of filming the video lecture. There is a tendency for video lectures with lower entropy to be perceived better.

Table of contents

Abbreviations used in the Thesis

DW – data warehouse
ETL – extract, transform, load or extraction, transformation and loading – one of the business intelligence processes
H – entropy (bits)
kHz – frequency unit, kilohertz
Liepu – University of Liepaja
LZW – Lempel-Ziv-Welch data compression algorithm
NSTI – National Institute of Standards and Technology of the United States
RTU – Riga Technical University
RLE – run-length encoding
Covid-19 –coronavirus disease 2019 – an infectious respiratory disease caused by the SARS-CoV-2 virus

Introduction

A video lecture is a lecture in the form of a video that offers educational material on a topic to be learned. Whether you are five or ninety-five, the Internet has much to offer today. Especially if the topic you are looking for is education, then the resources seem endless. E-learning platforms such as Coursera, Khan Academy, Open Culture Online Courses, Udemy, and online learning platforms used major universities such as Harvard, Yale and Berkeley, and other world-class universities, containing thousands of subjects based mainly on publishing video lectures show the topicality of this topic.

Also in Latvia, already in 2012, the auditoriums of Riga Technical University were modernly equipped for recording video lectures and placing video materials on the adapted Moodle e-learning platform. E-learning platforms started to be used also in the University of Latvia, Riga Stradiņš University, as well as in general education schools, using their own or the e-learning platform solution offered by eduspace.lv.

The aim of the Thesis is to analyse various study materials –lecture recordings from the audience and prepared study materials that are filmed as additional study materials. Blended learning makes the learning environment flexible, as knowledge and information for learning are always available – anytime, anywhere.

The tasks of the Thesis. The author wants to obtain quantitative information on what is an easy-to-understand video lecture. Since entropy is the most important quantitative measure in communication theory, which is widely used not only in communication technology, but also in business intelligence, advertising, linguistics, and elsewhere, it is logical to apply it to the characterization of video lectures as well, which, as far as I know, has not been done so far. The Thesis examines how the qualitative guidelines for good video lectures defined in previous studies by other authors affect entropy and how entropy correlates with the type of video lecture. The video lecture is analysed as a (optical and acoustic) code. Different codes correspond to different video lessons. The Thesis analyses the impact of the guidelines on these codes in order to make them as understandable as possible for students.

The term "video lecture" is used to cover a wide range of exposure styles. The author defines 11 different styles of materials that can be defined as a video lecture. However, the question arises as to which of these is most easily perceived by the viewer.

The author chose the topic of the research for two reasons. Initially, the author wanted to link the Thesis with video lectures, as within the framework of the Erasmus program, as an employee of Riga Technical University, the author visited the Polytechnic University of Valencia in Spain and made video recordings in studios on specific topics.

The second reason is that distance learning, e-learning, and online study courses at various popular universities around the world are becoming increasingly widely used. During the Thesis research the world was under the Covid-19 pandemic. Not only universities, but also secondary and primary schools were moving to distance learning. The content that was created was mainly created spontaneously to cover the substance and provide information, rather than thoughtfully, because no one was ready and prepared for such a situation. However, it has also given people the opportunity to test their abilities in distance learning and more time to focus on distance learning.

Although various studies have been conducted, there are no specific rules or guidelines for designing video lectures to be as effective as possible (Chandler, 1991). Each lecturer or each university can create or record lectures as they wish. However, for students, this is important. Therefore, the author wanted to study this topic, because universities in Latvia are still beginners in this field, and if there were any guidelines or more detailed information about what a video lecture should be to make it easier for students to understand, teachers and students would benefit, as well as universities.

Attention should also be paid to the changing generations of active students. If ever, for the so-called Millennium generation, a Power Point presentation prepared with lectures was enough, then now, in order for the information to reach the existing Z[1] generation students, the lecture must use various, including interactive, elements to present the content (Rubene, 2020).

However, video materials should be such as to reduce the cognitive load and optimize student memory usage (Chandler, 1991).

The next question that arose was how to find out how good and information-rich the video lecture is and how to measure it. How to measure the information provided by a video lecture? It is very difficult to define information.

There is no precise and universally acceptable definition of information. But there is quantitative theory of as it called syntactic information created, that successfully describes transmitting and receiving of the information in communication channels.

The material carrier of the information is a signal. A signal is a physical process whose parameter change reflects the information being transmitted. An information signal is used to transmit information. The information signal is formed by the source of the information, changing the signs corresponding to the information to be rejected.

In 1948, K. Shannon developed an information theory in his article "A Mathematical Theory of Communication" looking at the most important aspects of communication systems. The main features of this theory are, firstly, the great emphasis on probability theory and, secondly, the great

[1] Generation Z is the demographic group that follows Millennials and precedes Generation Alpha. Researchers and the popular media use the mid to late 1990s as the starting birth years and the early 2010s as the ending birth years.

importance of coding and decoding. Since then, information theory has been more refined, expanded, and more widely applied in practical communication systems.

Entropy plays a key role in Shannon's information theory – the average information per message from a message source. Shannon entropy is a number that depends only on the statistical nature of the information source. If the information source has a simple model, then the entropy can be calculated. Entropy is a measure of information from a source of information. The entropy described and analysed in this work is the Shannon entropy, which is measured in bits (Shannon, 1948).

In previous studies the author has performed entropy calculations for various written sources of information in Latvian, as well as looked for various correlations that would explain the changes in entropy.

The author has logically come to the topic of the Thesis, wanting to study a video lecture as an ensemble of optical and acoustic messages encoded in a certain way. The quality of the video lecture depends on the code of these messages. The author calculates the entropy of a video lecture and investigates whether the entropy of such a video lecture differs from the randomly selected video lecture by following the recommendations on which is the easiest video lecture for students and demonstrates that the structural information provided for the filmed lecture according to the recommendations is lower.

The aim of the study is to perform entropy analysis of video lectures to confirm the impact of easy-to-understand video lecture guidelines. Realizing this goal, it is possible to quantify the importance of recording a high-quality (taking into account the impact of the proven guidelines on students' perceptions) video lecture. The global goal of the work is to improve the quality of video lectures so that they are designed to be easier for students to understand.

The sub-goal of the study is to develop a method for calculating the maximum entropy for a video lecture. To achieve this goal, it is necessary to determine the effect of video and audio channels on entropy and total channel information.

Hypothesis The entropy of e-study video materials is determined by the type of video lecture used, the development technologies used, and predefined video lecture quality conditions.

Theses to be defended

1. The type of video lecture determines the entropy of the video lecture.

2. Entropy for a video lecture is a calculable quantity. The maximum absolute entropy carried by a natural lecture was calculated, which serves as the upper limit of the entropy of a video lecture, as well as other related maximum informative characteristics of the lecture – the information it carries, the information throughput capabilities of the lecture channel and its sub-channels.

3. The more precisely the guidelines are followed in recording the lecture, the lower the entropy of the video lecture. There is a negative correlation between the average video entropy of a lecture and the number of guidelines completed.

The characterization of the topicality of the research and the identification of the problem allow to formulate the **research questions**:

1. What is a video lecture that students can understand well?
2. How to calculate the maximum entropy for a video lecture?
3. Is there a relationship between the type of video lecture and the average entropy?
4. How to use the research results to improve the quality of video lectures?

In order to find answers to the research questions, the following tasks were set:

1. To analyse the scientific articles in order to create easy-to-understand video lecture rules or guidelines.
2. To calculate the maximum entropy of a video lecture.
3. To select different types of video lectures to analyse.
4. To determine the average video entropy, average spectral audio entropy and average temporal entropy of each video lecture.
5. To analyse and document results according to guidelines.
6. To provide suggestions for improving the quality of video lectures.

The limits of the research are marked by the subject of the research, which determines that video lectures filmed in different ways are analysed, both in the auditorium and in the video studio.

The research base consists of 11 video lectures (number as analysed).

Research methodology

1. Theoretical research methods:

1.1. Analysis of scientific and methodological literature – descriptive and comparison method.

1.2. Analytical calculation.

2. Empirical research methods:

2.1. Data acquisition methods:

2.1.1. Retrieval of data from the information system.

2.2. Data processing and analysis methods:

2.2.1. Method of graphical analysis programs used for classification and analysis of qualitative and quantitative research data – data processing program Matlab.

2.2.2. Graphical representation of data – Matlab and MS Excel.

2.2.3. Qualitative data processing.

2.2.4. Interpretation of quantitative and qualitative data.

The development of the Thesis was carried out in four stages:

• The first stage of the research (September 1, 2014 – September 1, 2015). Choice of research topic. Linking the existing research to the topic of e-learning and video lectures.

• The second stage of the research (September 2015 – September 2017).

Identification of research problems and contradictions, description of the topicality of the researched problem and research, research design development. In-depth analysis of the literature on video lecturing, the combined training module, its advantages and disadvantages, on the use of entropy in video analysis, as well as on technical solutions for entropy measurement. Selection and classification of scientific literature and sources. Development of video lecture recording recommendations.

• The third stage of the research (September 2018 – December 2020). Export of maximum syntactic information and entropy calculation. Drawing up a plan for further work. Analysis of video lecture viewing habits. Identification and selection of technical solutions.

• The fourth stage of the research (January 2020 – December 2021). Selection and analysis of video lectures. Analysis and interpretation of the results of joint research activities.

The pre-defence of the doctoral thesis at the faculty took place on January 27, 2022. The Thesis reviewer is Professor Atis Kapenieks.

The Thesis consists of an annotation, introduction, three parts, 12 chapters, 53 sections, results, conclusions, list of used literature and sources, as well as an appendix. The Thesis includes 57 figures and 20 tables. A total of 106 literature sources in Latvian and English are mentioned, but at least 5 times more were read during the research.

Scientific novelty and theoretical significance of the research

1. Output calculation of maximum information and entropy for video lecture.
2. An insight into the history and development of information theory is provided.
3. A summary of the study on the effect of different video lectures on students' perception ability.

Practical significance of the research

1. Guidelines for recording video lectures are provided.
2. A methodology for conducting video lectures as code analysis has been developed.
3. Possible innovative solutions in the evaluation of video lectures for the education of young people have been developed.

Author's contribution and approbation of research results:

The research described in the dissertation has been developed at the Faculty of Science and Engineering of the Liepaja University.

Data from the video lectures were obtained from the Polytechnic University of Valencia in collaboration with Carlos Turro Ribalta, Deputy Director of Network and Media Services. The adaptation of the Matlab program to determine the mean entropy was developed together with

Lauris Cikovskis, the Head of the HPC Centre of Riga Technical University and a leading researcher. The work was developed under the supervision of Professor Andris Ozols of Riga Technical University.

The results of scientific research have been published in scientific, peer-reviewed publications:

1. Alksne L., Cikovskis L., Ozols A. (2022). Entropy of video lecture (accepted for publishing in BJMC).
2. Alksne L., Ozols A. (2020). Maximum Structural Information Delivered by a Video Lecture. Latvian Journal of Physics and Technical Sciences, 2022, No. 2, pp.12–22.
3. Alksne, L., Jansone, A., & Bērzkalne, Z. (2019). Benefits from analyzing video lecture logs with leading business analytics tools. Baltic Journal of Modern Computing, 7(3), 393–404. doi:10.22364/bjmc.2019.7.3.06.
4. Alksne, L. (2016) How to produce video lectures to engage students and deliver the maximum amount of information. Society. Integration. Education Proceedings of the international scientific conference, Rēzekne, Volume ii, May 27–28, 2016, 503–516.
5. Bajarune, L., & Ozols, A. (2015). Latvian language as a code in different communication channels. Paper presented at the conference Environment, Technology, Resources, 3, 11–16. doi:10.17770/etr2015vol3.182.

1. Information theory

1.1. Information and its definition in communication theory

The theoretical part of the Thesis provides an insight into what information is and its definition in communication theory. The Thesis provides an explanation of how information is related to entropy, a key parameter that is determined and analysed in the research part. The transmission of information has played a huge role from the past to the present, so the Thesis also examines information coding, the origin and history of codes, as well as data compression. In this dissertation, the emphasis is placed directly on Shannon's information, which is used in communication channels, since the transmission of the content of a video lecture to its listeners and viewers can also be considered a communication channel. Shannon's information has been examined and analysed in the course of the dissertation, distinguishing it from analysing the content of information.

With the information exchange system, it is possible to regulate relations between individual members of society and their groups; it ensures the existence of a group of people in the external environment. Each individual receives or provides information about something when communicating. In Latin, the word “information” means explanation, outline. The system of information exchange in human society has developed so far that, since the beginning of the existence of mankind, artificial means of information exchange are widely used simultaneously with natural means of information exchange. By developing and perfecting artificial means of information transmission and exchange, man today has created a rich arsenal of technical means. The level of development of human society is largely characterized by the technical information exchange system at its disposal.

Information is one of the forms of existence of matter; it is an inherent feature of the material world. It can even be considered that there is information hidden in every state or development of the material world. The concept of information was strongly highlighted by such field of science as cybernetics. The word “cybernetics” comes from the Greek language. In translation, it means to manage the art. Nowadays, cybernetics is understood as the branch of science about the laws of information acquisition, storage, transmission and transformation and their study in complex systems. In the Middle Ages, this science was practically forgotten. The concept of cybernetics was re-used in the scientific works of the outstanding French scientist A. Ampère (1834). After Ampere's death (1836), it was forgotten again, while in 1984 the founder of modern cybernetics and information theory, the American scientist Norbert Wiener named his book “Cybernetics” after this little-known name. With the publication of this book in 1984, information theory began to develop rapidly.

The concept of information is usually associated with the existence of two objects – the source of information and the consumer. A precise and in all cases acceptable definition of information has not been created.

When studying the phenomena of nature and society that are related to information, and studying the properties of information, one comes across the concept of information in various aspects: one can be interested in information hidden in the meaning of individual words or their combinations (semantic or metrical information); information that characterizes the relative increase in knowledge of its recipient (pragmatic or syntactic information); information contained in various works of art (idealized information). The technical meaning of information is of great and practical importance, imagining information as symbolism used for communication purposes. Information is also defined as follows: “Information is information that is manipulated as an object by discarding, dividing, transforming, storing, or directly using it”.

The material carrier of information is a signal. A signal is a physical process, the change of a parameter of which reproduces the transmitted information. An informative signal serves to transmit information. The informative signal is formed by the source of information, changing the signs corresponding to the rejected information. Letters written in sequence can serve as signs. A message is a set of signs that conveys the information to be transmitted. The ensemble of the message is numbers, alphabet, etc. The sequential arrangement of a message ensemble constitutes a message. So, the informative signal is used to transmit a message or report. The receiver of the signal perceives the signal as a message, further the message is transformed into information that is received by the information consumer. The process of transforming information into a message is called encoding, and the opposite process is called decoding.

Communication is the exchange of messages – communication. In the transmission of technical information, the main elements of the general communication scheme are the source of the message, the communication channel and the recipient of the message. Such a system is intended for the transmission of an informative message (Grabinskis, 1984).

Conclusions

1. A general idea of the concept of information is given.
2. The basic concepts of syntactic information are defined – sign, message, signal, coding and decoding.

1.2. K. Shannon's definition of a discrete message ensemble

In 1948, K. Shannon developed an information theory in his article “A Mathematical Theory of Communication” in order to mathematically look at the most important aspects of communication systems and to get an opportunity to optimize communication systems. The main variables of this theory are, firstly, the great emphasis on probability theory and, secondly, the importance of the encoder and decoder. Since then, information theory has been more refined, expanded, and more widely applied in practical communication systems.

Shannon plays a key role in the way information is transmitted and stored. Shannon completely ignores whether the text is meaningful, understandable, correct, incorrect or irrelevant. Similarly, questions about who sends the information and who is the receiver are excluded. According to Shannon's theory of information, it is irrelevant whether the text is sequential and significant or whether the letters are chosen for good fortune. A paradox emerges here: fortunately, selected letters reach a maximum in the content of the information, but where the text is more meaningful and linguistically diverse, it corresponds to a lower value (Garcez, 2011).

Teletype[2] and the telegraph are the two simplest examples of information transmission on a discrete channel. Discrete channel means a system where a finite number of elementary symbols $S_1,\dots, S_n$ are transmitted from one point to another. Each symbol S_i corresponds to a signal with a duration of seconds.

In the case of a teletype, where all signals have a single transmission duration and any order of 32 symbols, this means that each symbol represents 5 bits of information. If the system transmits n symbols per second, then we can say that the channel throughput is $5n$ bits per second. This does not mean that the teletype channel will always transmit at this speed – it is the maximum speed, whether the maximum will be reached and what the transmission speed will be depends on the source of information (Shannon, 1948).

The definition of a discrete channel is only one-fifth of Shannon's paper, further definitions are given for a discrete noisy channel, a continuous transmission channel, and various theorems and calculation formulas (Carlson, 1986;Ozols, 2005).

[2] Teletype – a set of devices such as ribbon punches and page printers used in telecommunications.

1.3. The main characteristic measures of message ensemble

Entropy is the average information per message per message ensemble. Examples of messages are letters, words, pictures. Information carried by one message if an ensemble of messages is given a_1, a_2, ... a_n with probabilities p_1, ...p_n defined as

$$I\left(a_k\right) = \log_2 \frac{1}{p_k}.$$

The throughput of a communication channel is equal to the maximum possible data rate.

$$C = R_{\max}$$

where C is the channel throughput and is transmission speed.

$$R = \frac{\partial I(t)}{\partial t} \quad (1)$$

1.3.1. Entropy

Entropy is a quantitative measure of situational uncertainty that is widely used in thermodynamics and information theory. The concept of entropy is used in various studies of problems of optimal coding of information. The concept of entropy in information theory describes how much randomness there is in a signal or random event (Fig. 1.3.1).

Claude E. Shannon proved in his article "Mathematical Theory of Communication" that there is a certain limit to the compression of information without loss. This limit is the entropy, denoted by H. The H value of entropy depends on the source of information. To compress information without loss, the compression ratio must be close to the entropy value.

Entropy is a number that depends only on the statistical nature of the source of information. If the information source has a simple model, then the entropy can be calculated.

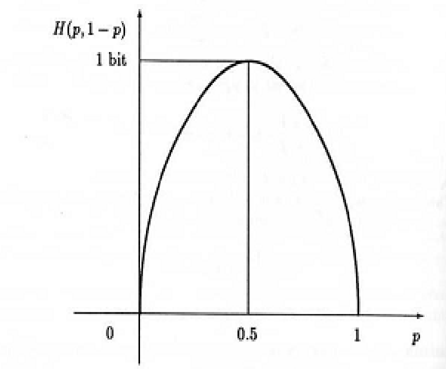

Fig. 1.3.1. Dependence of entropy on probability in the case of an ensemble of two messages.

Choosing an arbitrary message ensemble $X = (X_1, X_2, X_3, X_4 .....)$, which is text, and messages are letters, it is possible to compute several orders of entropy. Each layer is different in that the higher the order, the more adjacent letters per letter are calculated.

Properties of entropy H:

1) $H(X) \geq 0$;
2) entropy is an additive value for two independent message ensembles X and Y

$$H(X + Y) = H(X) + H(Y); \qquad (2)$$

3) entropy is a finite value $H \leq H_{max} = \log_2 N$, where N is the number of messages in the ensemble.

Zero-order entropy is calculated by the formula

$$H(0) = H_{max} = \log_2 N \text{ bits/symbol} \qquad (3)$$

If N is the number of letters in the alphabet, then the space is also taken into account when calculating the entropy of a written language. In this case, the letters are assumed to be independent of each other. $H(0)$ is also considered as $H(\max)$, because the entropy of any order cannot be higher than the entropy of zero order.

The entropy of the first order is calculated by the formula

$$H(1) = \sum_{i=1}^{m} p_i \log_2 p_i \text{ bits/symbol,} \qquad (4)$$

where p_i is the probability of the message (symbol), again in this case they are independent of each other.

The second order entropy is calculated by the formula

$$H(2) = \sum_{i=1}^{m} p_i \sum_{j=1}^{m} p_{j|i} \log_2 p_{j|i} \text{ bits/symbol,} \qquad (5)$$

where $p_{j|i}$ is conditional probability for the report j, if the previous one was, for example, a letter; however, the message does not have to be a letter. It can also be, for example, a pixel. To calculate the second-order entropy, the symbol before the symbol, or all possible combinations of the two symbols, must be taken into account.

The entropy of the third, fourth and higher order is calculated according to the same formula, only with each order more messages before the correspondingly defined message are taken into account (Latvian Academy of Sciences, 2015).

The minimum entropy is $H(X) = 0$, and is achieved by those messages for which the probability of the information provided is equal to 1. Maximum entropy n – symbol for the message A is $H(X) = \log_2 m$ bits and is reached if the symbols have the same probability (Jehonovičs, 1984)

$$p_i = \frac{1}{m}. \qquad (6)$$

In the case of smooth transmission in a silent channel

$$R = \frac{H(X)}{\tau}, \qquad (7)$$

where τ is the average transmission time per message. In case of inconsistent transmission

$$R = \frac{\partial I(t)}{\partial t}.$$

1.3.2. Mutual information

The mutual information between two discrete, freely chosen variables is denoted as $I(X,Y)$. Mutual or relative information is a quantity that indicates the amount of information shared between the input and output of a noisy channel. Mutual information is measured in bits.

So mutual information is a measure of information between X and Y. If X and Y are independent, then X contains no information about Y, and vice versa, in which case their total information is zero. If X and Y are identical, then all the information sent to X is shared with Y. If X receives no response from Y, and vice versa, then the total information is equal to the information sent by X (or Y) itself, called the entropy of X (Latvian Academy of Sciences, 2015).

Mutual information is calculated as follows:

$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X) \qquad (8)$$

The maximum value of the mutual information is equal to the bandwidth of the noisy information channel (bits/symbol).

Characteristics of mutual information:

1. Mutual information is symmetric

$$I(X;Y) = I(Y;X).$$

2. Mutual information is always non-negative

$$I(X;Y) \geq 0.$$

3. The mutual information is related to the total input and output entropy of the channel as follows:

$$I(X;Y) = H(X) + H(Y) - H(X,Y). \qquad (9)$$

Relative information is used in the case of noisy communication channels to determine the information throughput, as well as to define the speed of information transmission (Carlson, Bruce, 1986):

$$R = \frac{H(X,Y)}{\tau}. \qquad (10)$$

1.3.3. Redundancy

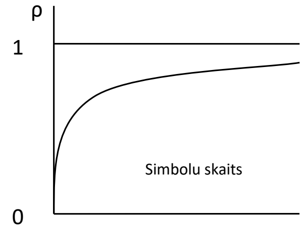

Fig. 1.3.2. Redundances atkarība -no saistīto ziņojumu skaita *n* ansamblī.

By calculating the entropy, it is also possible to calculate the redundancy of the message source

$$\rho = 1 - \frac{H(A)}{H_{\max}(A)} = 1 - \frac{H_n(A)}{H_0(A)} \qquad (11)$$

Informational redundancy means the inclusion of duplicate or additional data in system data arrays, the removal of which does not reduce the adequacy of these arrays for the real objects they describe (11). Redundancy in information theory is the number of bits used to send a message minus the amount of actual information in bits. Data compression is a way to eliminate unwanted redundancy, but if a message has to be transmitted over a noisy channel with limited capacity, then redundancy is desirable. So, redundancy, for example, in our language are the words that we say, but even without these words the information would be understandable. We can make sure of this every time we send a text message, trying to say as much as possible with as few symbols as possible, so that only one text message comes together – words, letters are omitted or even written without spaces, but the text is still understandable.

Example: Tksts bz ptskņm. Tekstsbezatstarpēm. If from this text we can reconstruct the meaning of these sentences written without vowels and without spaces, it means that these vowels or spaces are redundant for this message.

However, redundant words or letters are what allow us to understand information when, for example, we speak in a noisy place. "Where is the salt package?" If, while saying this sentence, a noisy heavy truck will have passed by, "salt" may sound like "clay" or "far", but the redundant word "package", will make you understand the question though. This may be a very primitive example, but in most cases, if one word is missing in a sentence, then we will be able to guess the missing word, if a letter is left out, then it is almost certain that we will guess it.

Saksaņā ar kdāas agnļu uvinersiātetes pjuētīmu, nav sravīgi kādā scbeīā ir srākatoti bturi vādrā, veigīni savgīri lai primias un pdējēais butrs btūu sāavs vtieās. Pēārije var būt plnīīgi saukjati un jūs jjooprām vēiearst lsīat bez pomblrēām. Tas ntoeik tēpāc, ka pabestiīa mēs nāealsm kratu btruu atšseiķvi, bet gan vrādu kā vneiu velesu.

In text above in Latvian but with changed sequence of letters (except the first and the last) it is written that according to the research of University in England, sequence of the letters in the word is not so important as long the first and the last letter is in the right place. All the other letters can be completely in random order but you can still read the text without problem. It is because we do not read every letter separately but the word as one ((Rayner, 2006)

If 50 % of the language is redundant, then it would be possible to save 50 % of the investment required for the electronic transmission of messages in that language. Something similar happens when a file is compressed, but if some noise occurs somewhere in the transmission and one of the symbols contained in the compressed file is destroyed, then it is impossible to restore the original file.

In the digital encoding of messages, redundancy plays an important role, using encoding with the even number of ones. The letter A corresponds to 01000001 in the binary system. So, to transmit the letter A we need 8 bits, we need to transmit these eight characters. But if the line is messed up and an error occurs and we get 010000?1, we can no longer tell what letter it is. It can be A if the missing character is 0, but if that character has been 1, then it has been the letter C. Of course, in a normal context we would have no problem understanding this, but what if redundancy has already been applied and the file is compressed? In that case, adding a parity bit, which would be another redundant bit, would overcome the problem. If the sum of the numbers is an even number, then 0 is added, and if it is odd, then – 1. So, getting 010000?1**0,** the added zero in front tells us that we should have received A (010000**0**1); if we received 010000?1**1**, then the attached 1 says that the received letter is C (010000**1**1). If a really noisy channel is expected, it is possible to agree to send parity bits every 4 bits. It may seem unnecessary to send redundant bits that are not really needed. But if we had compressed the text from 10,000 characters to 8,000, excluding redundant symbols, one parity bit should also be added to each sent character – that would be 8,000 parity bits. 8000 bits is equivalent to 1000 characters, which means it is more convenient (Underwood , 2006).

This method is the corrective code, which is also discussed in Section 5.3 of the Thesis.

Redundancy is closely related to the compressibility factor that is calculated as follows:

$$r = \frac{H(A)}{H_{\max}(A)} = \frac{H_n(A)}{H_0(A)} = 1 - \rho \ . \tag{12}$$

2. Entropy of language

Natural language is one of the main means of communication. As a sign system, it is a tool for conveying and disseminating information. With the help of its system of signs, symbols and the laws of their combination, connection and composition, language is a unique communication code, according to which other non-verbal codes are also used.

Since its beginnings, language is also a means of accumulating information and creates a structure and a "navigational system" for the stored information. That is why language creates conceptual and even perceptual laws. Language as a means of communication is an open code with special development laws.

In an information-cluttered space, where modern technology enables close interaction between people located at great distances from each other, and where information flows and is exchanged at speeds similar to those of today, the approach to studying language and establishing norms for natural language must also change, so that language would develop not as an abstract means of abstract communication, but as a rich, creative tool that can be used to store and pass on information about the new and rapidly changing reality. Therefore, not only studies of language use, grammar, syntax and style are necessary, but it is also important to pay attention to the statistical properties of the language (Papadimitriou, 2010).

While writing her bachelor's thesis on the topic of language entropy, the author unfortunately had to conclude that there are no studies or calculations on the entropy and static properties of our language. Whereas, English and Russian speakers have studied their language very carefully – they have made calculations for various genres of literature –poetry, novels and telegrams. There are also entropy calculations performed at very high arrangement levels, in Russian even up to the eighth. In her bachelor's thesis, the author calculated entropy for a press communication channel, and in her master's thesis for various sources, so that they could be compared, and looked for connections between the genre in which the work was written and the entropy number.

Table 2.1

Language Entropy

$H(N)$	English	Russian
$H(0)$	4.75	5
$H(1)$	4.07	4.05
$H(2)$	3.36	3.52
$H(3)$	2.77	
$H(8)$		2

Shannon obtained such numbers by analyzing 7 literary works. Before preparing calculations, uppercase letters were converted to lowercase, all numbers and special characters were removed, totaling 5086936 symbols (Kulkarni, 2002). Entropy of languages will be discussed further in Chapter 5.

The author concludes that the application of entropy is very wide. It can be used in a wide variety of industries and on various information carriers.

Conclusions

1. The use of Shannon's entropy in business intelligence processes is examined in detail. Its importance is highlighted.
2. The role of entropy as a measure of information security has been analysed.
3. The importance of language entropy in linguistics is considered. It has been established that the entropy of the Latvian language has not been calculated and analysed until the author's works. This will be done further in the Thesis statement.

3. Comparison of the Latvian language as a code in various communication channels

Since the video lecture contains a sound channel where the language is spoken, let us consider the language as a code. Specifically, the Latvian language. Any language is a code with which people encode information for mutual communication. Let us look at written language.

In language, a message can be considered:

1) letter,
2) name,
3) a sentence.

In Latvian, a sound corresponds to a letter, so a letter can be considered a code symbol that corresponds to a message – a sound.

I chose the letter as the code symbol that represents the code, because the letter is the basis of the language. Language is like a code to convey information, and letters are combinations of codes to encode information.

The author chose to compare entropy, taking Latvian language texts from the press channel (three articles), literary sources, and laws written in Latvian.

A program was created to perform the calculations. The program is designed in the form of an internet website, the programming language used is *php*, and the *html* language is also used. All calculations were made using a *php* script and the *MySQL* database management system, located on the *Apache* web server (web.hc.lv, 2008).

Program script is presented in Appendix No. 1

Principle of operation of the program:

1. The text to be analyzed is written or copied in the form of adding the text (Fig. 3.1).

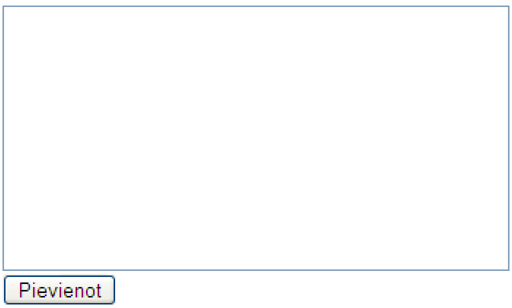

Fig. 3.1. Program window.

After entering the text, press the “Add” button.

2. The program replaces all uppercase letters with lowercase letters, all punctuation marks are removed and spaces are replaced with the symbol “_”.

3. The text is processed by extracting combinations of three letters, combinations of two letters and letters one at a time. When analyzing the text, the program records each new combination in the database, but if the combination is found again, the number of recorded combinations in the database increases by one.
4. When the text analysis is finished, the number of obtained combinations is put into the formulas to calculate the first, second and third order of text entropy, that is, the results $H(1)$, $H(2)$ and $H(3)$ are the output.

The maximum entropy of the Latvian language is calculated according to the formula:

$$H(0) = \log_2 m \text{ bits/symbol,} \tag{20}$$

where m is the number of letters in the alphabet and a space, in Latvian $m = 33 + 1$

$$\boldsymbol{H(\mathrm{max}) = H(0) = 5.0875 \text{ bits/symbol}}$$

The first-order entropy formula is as follows:

$$H(1) = -\sum_{i=1}^{m} p_i \log_2 p_i \text{ bits/symbol,} \tag{21}$$

$$p_i = \lim_{N=\infty} \frac{N_i}{N} \tag{22}$$

where p_i is the probability of a symbol appearing, that is, the number of a single symbol against the total number of symbols in the text if the number of these symbols is large.

In order to calculate the second-order entropy $H(2)$, p_i – the probability of the appearance of the symbol i should be inserted into the formula, $p_{i|j}$ – the probability of the appearance of the symbol if there is another certain symbol j before the symbol i, that is, the number of combinations of the two letters i and j against the number of the symbol i, whose probability of occurrence is calculated.

$$H(2) = -\sum_{i=1}^{m} p_i \sum_{j=1}^{m} p_{j|i} \log_2 p_{j|i} \text{ bits/symbol} \tag{23}$$

$$p_{j|i} = p(a \mid a_i) = \lim_{N_j \to \infty} \frac{N_{i|j}}{N_j} \tag{24}$$

The third-order entropy $H(3)$ is calculated according to the following formula:

$$H(3) = -\sum_{i=1}^{m} p_i \sum_{j=1}^{m} p_{j|i} \sum_{k=1}^{m} p_{k|j,i} \log_2 p_{k|j,i} \text{ bits/symbol} \tag{25}$$

$$p_{k|j,i} = p(a_k \mid a_j \cdot a_i) = \lim_{N_{ji} \to \infty} \frac{N_{k|ji}}{N_{ji}} \tag{26}$$

Here, p_i and $p_{i|j}$ are the same values as in the case of $H(1)$ and $H(2)$, but $p_{k|i,j}$ is the probability of conditional appearance of symbol k, if symbol k is preceded by symbols i and j, that is, a combination of three symbols versus a combination of two symbols, the number preceding the symbol whose probability is calculated at p_i.

Since the program is designed to be used an unlimited number of times, I selected the texts from each of the categories I initially selected; the text fragments have approximately the same number of symbols.

Results:

- Education Law (5069 symbols) (www.likumi.lv)

***H*(1)** = 4.349815972854

***H*(2)** = 2.923080865874

***H*(3)** = 1.5184876867063

- Labor Law (5055 symbols) (www.likumi.lv)

***H*(1)** = 4.2634495552793

***H*(2)** = 3.0348646651092

***H*(3)** = 1.7572303727057

- Forest Law (5075 symbols) (www.likumi.lv)

***H*(1)** = 4.280832823845

***H*(2)** = 3.1072458132097

***H*(3)** = 1.6503462658157

- Rainis, "*Tālas noskaņas zilā vakarā"* (5042) (Rainis, 1903)

***H*(1)** = 4.1655032631897

***H*(2)** = 3.08465847253

***H*(3)** = 1.9725815401199

- A. Pumpurs "*Lāčplēsis"* (5052) (Pumpurs, 1888)

***H*(1)** = 4.1902519411154

***H*(2)** = 3.0167031089157

***H*(3)** = 1.8641893821756

- R. Blaumanis "*Salna pavasarī"* (5057) (Blaumanis, 1958)

***H*(1)** = 4.2996599130587

***H*(2)** = 3.3166620129879

***H*(3)** = 2.1391020983167

- Brothers *Kaudzītes* "*Mērnieku laiki"* (5014) (*Kaudzītes,* 1879)

***H*(1)** = 4.3218684830753

***H*(2)** = 3.3380220823268

***H*(3)** = 2.2467898718413

- The text analyzed in the bachelor's thesis from the newspaper "5 minutes"

***H*(1)** = 4.4171518380824

***H*(2)** = 3.3706035633218

***H*(3)** = 1.9541757696007

- "*Diena*" *(Diena*, 2008)

***H*(1)** = 4.3788652103022

***H*(2)** = 3.3894964595281

H(**3**) = 2.2223302874547
- "LETA" (LETA, 2008)
H(**1**) = 4.3883573930156
H(**2**) = 3.3656853313569
H(**3**) = 2.0605372669881

Figure 5.2 shows graphical calculation results for all three orders of entropy, that is, $H(1)$, $H(2)$ and $H(3)$. It can be seen that texts of the same type have similar entropy.

The texts from press sources and prose works have the highest entropy, which can be explained by the use of a rich vocabulary. Law texts follow, in this case the Forest Law has a very high entropy, which is very often due to the letter ž used in this law – 37 times, thus creating combinations with the letter ž, which are not often used if the content of the text is different, for example, In the Labor Law, the letter ž appears only 3 times. Figure 3.3 shows a comparison of combinations with the letter ž when calculating the second-order entropy in the Labor Law and the Forest Law.

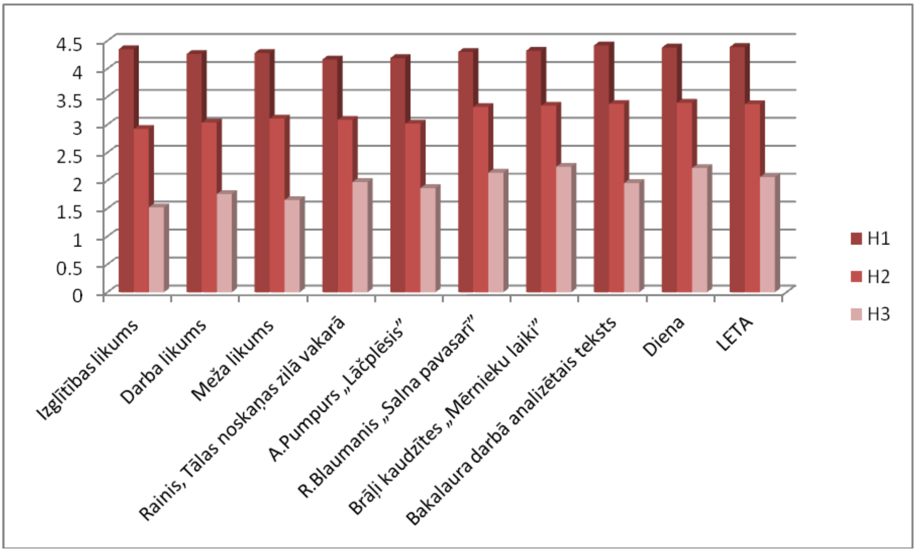

Fig. 3.2. Calculated entropy.

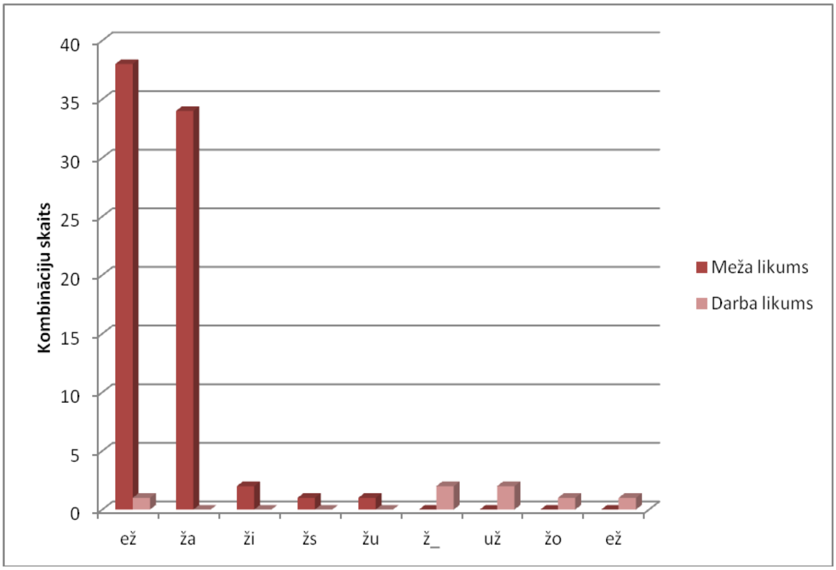

Fig. 3.3. Combinations of letter *ž* in *H*(2).

Figure 3.4 shows a comparison of combinations with the letter *ž* when calculating the third-order entropy for these two laws.

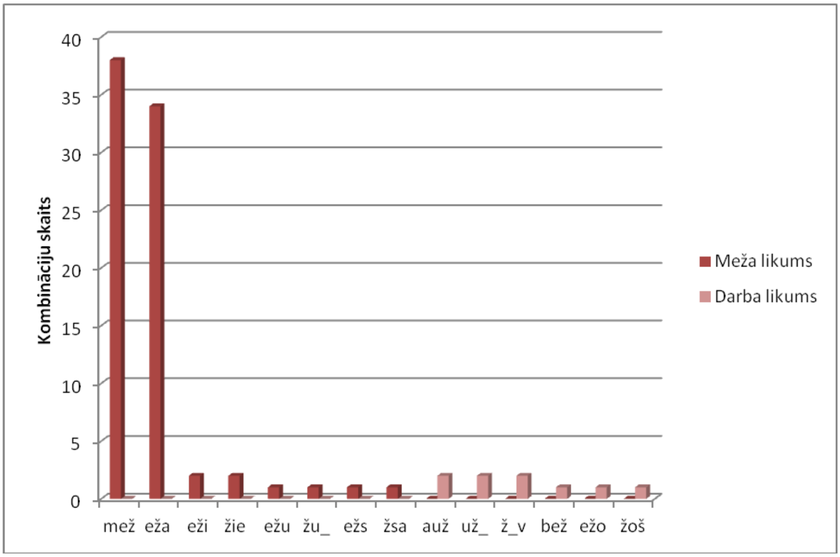

Fig. 3.4. Combinations of letter Ž in H(3).

In Fig. 3.3, which shows the combinations of *H*(2), the most frequently seen combinations of urchin and ža form sums of 0.0208197308569 and 0.00108960894717, respectively. In the Forest Law, ž_ and už are combinations that occur more often in the Labor Law, they form the summable

0.000233844693472 and 0.00263838210761. Although here for the combinations ža and už, the sum in the Forest Law is less than that in the Labor Law, however, they do not need to be compared, because in the combinations it is important in which position, the first or the second, the letter ž is located.

Poetry and epic fragments gave the lowest value of entropy $H(1)$. While researching the obtained combinations, I compared the poetry of Rainis and R. Blaumanis' "*Salna pavasarī"*. In poetry, the number of combinations for letters was greater, both two and three times, however, in the prose work, combinations are repeated much more often and in different ways, which ultimately creates the greatest entropy.

The average obtained entropy by genre can be seen in Fig. 3.6. The first-order entropy shows that the press channel has the highest entropy, followed by laws, then prose, and the last is poetry. However, the second-order entropy is the lowest for laws, and the highest for press and prose. The second-order entropy shows the dependence of one letter on the preceding letter. The higher the entropy, the higher the probability of a two-by-two combination of letters. The third-order entropy calculates the sum of the probabilities if the occurrence of one letter depends on two preceding letters. Laws have the lowest third-order entropy, followed by poetry; and prose has the highest entropy. The lower the entropy, the higher the compressibility or redundancy. The lower the entropy, the easier it is to predict which letters will follow each other. The more letters are "discovered", the more the entropy decreases, as the sequence of letters is easier to predict.

A game has been created based on Shannon's definition of entropy, where you have to guess letters to remember words. Entropy is determined by how quickly a sequence of letters is remembered. Figure 3.5 shows the author's attempt to play the game. The results would be better if the game was in Latvian, because it was difficult to remember the last word due to ignorance. The task is to successfully remember the next letter, knowing only the previously remembered one. Claude E. Shannon considers the sequence of number of letter guesses to be the cipher of a sentence and evaluates the entropy of the experiment as the entropy of English letters (Kozlowski, 2008; Mika, 2008).

Unfortunately, only a description of the game remains on the website https://mathweb.ucsd.edu/~crypto/java/ENTROPY/, but the entropy calculator is used for the principle of the game.

Fig. 3.5. C. E. Shannon's experiment for calculating entropy.

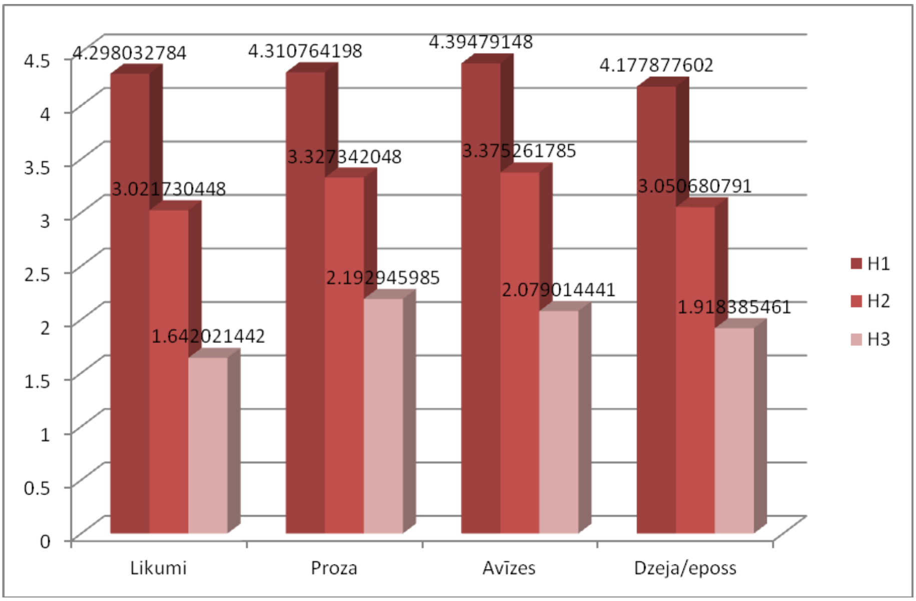

Fig. 3.6. Average entropy by genre.

The average entropy results for all used texts for which entropy was calculated can be seen in Fig. 5.7.

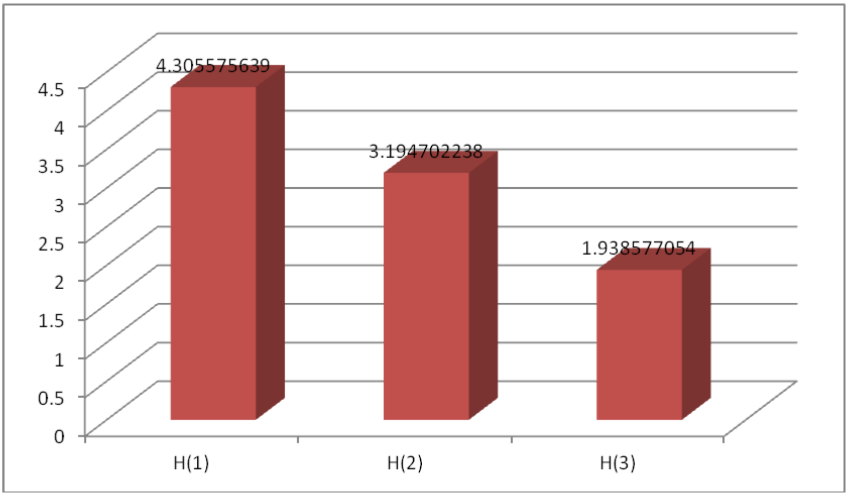

Fig. 3.7. Average entropy by orders.

Table 3.1

Comparison of Entropy

$H(N)$	Latvian language	English language	Russian language
$H(0)$	5.0875	4.75	5
$H(1)$	4.3056	4.07	4.05
$H(2)$	3.1947	3.36	3.52
$H(3)$	1.9386	2.77	

Table 3.1. shows the entropy of the Latvian language, calculated by the author, C.E. Shannon's score for English, and a teacher's information on Russian entropy. The entropy of the Latvian language is higher because there are more letters in the Latvian language, but it falls faster because the combinations are repeated less often, thus the compressibility is higher.

Based on the obtained entropies, it is also possible to calculate the redundancy (Table 3.2) and the compressibility factor. These parameters are more precisely defined, the higher order entropy is used for calculations. Redundancy:

$$\text{At } H(1)\ \rho = 1 - \frac{H(A)}{H_{\max}(A)} = 1 - \frac{H_n(A)}{H_0(A)} = 1 - \frac{4.3056}{5.0875} = 0.1537 = 15.4\,\%$$

$$\text{At } H(2)\ \rho = 1 - \frac{H(A)}{H_{\max}(A)} = 1 - \frac{H_n(A)}{H_0(A)} = 1 - \frac{3.1947}{5.0875} = 0.3720 = 37.2\,\%$$

At $H(3)$ $\rho = 1 - \frac{H(A)}{H_{\max}(A)} = 1 - \frac{H_n(A)}{H_0(A)} = 1 - \frac{1.9386}{5.0875} = 0.6189 = 61.9\%$

Table 3.2

Comparison of Redundancy

ρ *H*(*N*)	Latvian language	English language	Russian language
ρ *H*(1)	15.4 %	14.3 %	19 %
ρ *H*(2)	37.2 %	29.2 %	29.6 %
ρ *H*(3)	61.9 %	41.7 %	

Comparing the redundancy of the Latvian language with the English and Russian languages, it can be seen that the Latvian language has the highest redundancy. This can be explained by both length marks and softening marks, as well as the already mentioned vowels, without which the Latvian language is also intelligible. Higher entropy can be achieved if there is a higher diversity, that is, the combinations are repeated differently, this also increases the redundancy. If the most used combination is omitted, it could be perceived in the same way. For example, replacing the word "*izglītība*" with "*izglīt*" in the Education Law would immediately allow getting rid of several combinations, but would be understandable in all inflections.

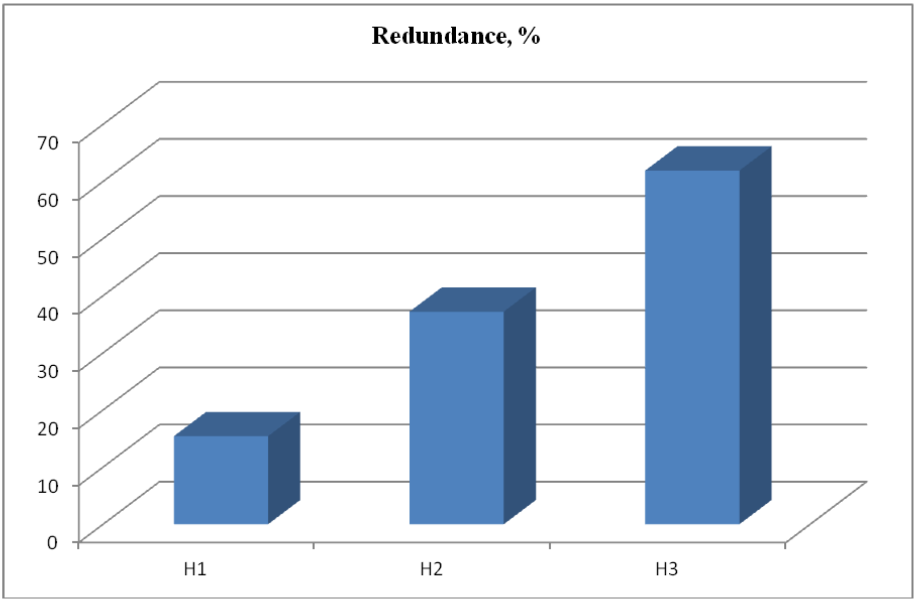

Fig. 3.8. Redundancy at *H*(1)*,* *H*(2) and *H*(3).

To determine what the most accurate redundancy would be, at what $H(N)$ it should be calculated, the length of the middle word had to be determined. The author chose the text by R. Blaumanis "*Salna pavasarī*" and manually calculated the average word length. That is, 4.52, rounding should calculate $H(5)$ to calculate the most accurate redundancy for the Latvian language. See Fig. 3.9 for the distribution of the text by word length (Bajarune, 2015).

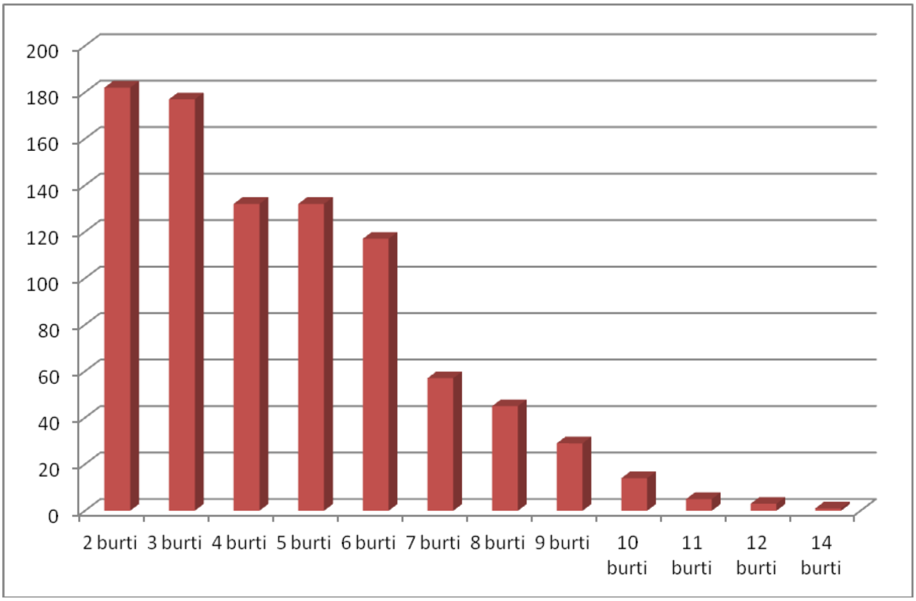

Fig. 3.9. Division of words by length.

Compressibility coefficient:

$$\text{At } H(1) \;\; r = \frac{H(A)}{H_{\max}(A)} = \frac{H_n(A)}{H_0(A)} = 1 - \rho = 0.8463;$$

$$\text{At } H(2) \;\; r = \frac{H(A)}{H_{\max}(A)} = \frac{H_n(A)}{H_0(A)} = 1 - \rho = 0.628;$$

$$\text{At } H(3) \;\; r = \frac{H(A)}{H_{\max}(A)} = \frac{H_n(A)}{H_0(A)} = 1 - \rho = 0.3811.$$

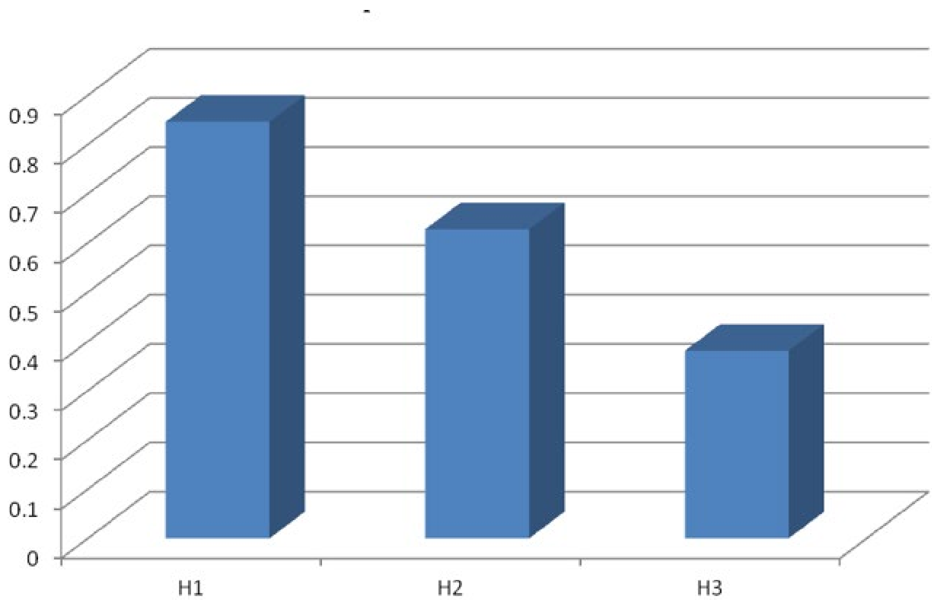

Fig. 3.10. Compressibility coefficient at *H*(1), *H*(2) and *H*(3).

Conclusions

1. For the first time, the Latvian language has been quantitatively analyzed as a code in various texts. A comparison of the entropies of different texts was made.
2. The entropies of the Latvian language have been compared with the entropies of the English and Russian languages. It is shown that the redundancy in the Latvian language texts is greater than that in the English and Russian languages because length marks and softening marks are also used.

4. Information from records of students' video lecture viewing activities

In this research, the author has analysed data from two journals of the UPV (Universitat Politècnica de València) video lecture recording system.

The first log is from years 2016/2017 and the second from 2018/2019, both from the first semester (September – January). Logs have two types of registers – actions and traces. Actions are video player actions, so they appear after the user does something. They are mostly understandable. Actions and traces are register names, so they must be separated somehow.

Footers are periodic information that the player sends along with the part of the video being viewed. Traces are not triggered by user-triggered events because the user can close the Internet browser or the window with the video and then the log would lose all the last information, so the logic behind it is to divide the data into time intervals. They go from point to point in seconds. Inpoint and outpoint are the number of seconds in the video where the action occurred. Events (like PLAY) will both be the same. "Course_id" is the course (UPV starts the semester in February) and "Mediapackage" is the video ID. Course id is series_id. So, the media packages (videos) belong to the course (series_id).

The first one that the author has analysed is a video viewing session, which is a single instance where a student watches a specific video. An average video viewing session is determined, which is the average time spent on a video lecture. This is a key characteristic of engagement, the amount of time a student spends on a video (i.e. the length of a video viewing session). Engagement time is a standard metric used by free video providers like YouTube and enterprise providers like Wistia. However, its limitation or inaccuracy is that it cannot detect whether the student is actively paying attention to the video or is simply playing it in the background while doing side tasks (Guo, 2014).

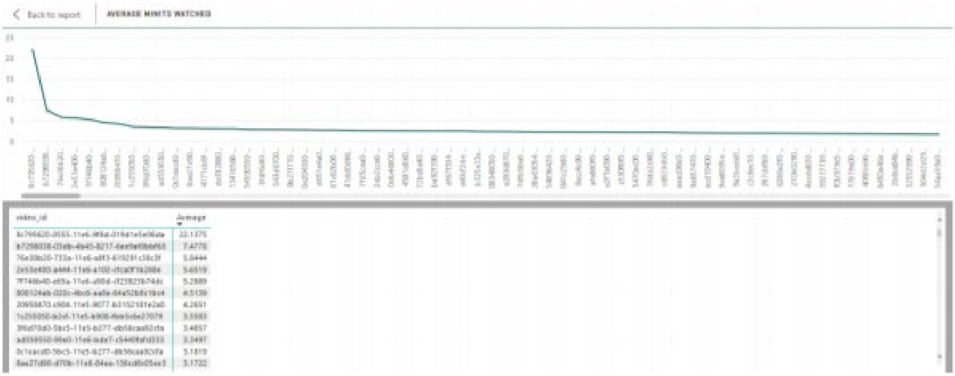

Fig. 4.1. Video viewing times; average viewing times in minutes are shown on the y-axis and video lecture IDs on the x-axis. The table below the schedule shows the id of the video lectures and the average viewing time in minutes related to the start of the schedule.

As can be seen in Fig. 4.1, where the function and the average video viewing times obtained with Power Bi are displayed, the author has obtained very useful information, which the author has already mentioned in the video lecture filming guidelines, that it is better to divide the lecture into 5–10 minutes, for the topic corresponding videos, as this is the average length of time a student watches a lecture without interruption. To look for deeper connections, you should know more about the video.

In Fig. 4.2. the author was able to find and display information about when students watch video lectures – whether during the work week or more on weekends. Is this time the same throughout the semester or are students more active when exams come, at the end of the semester.

It was also interesting to learn about the interruption of the video lecture – there is a certain connection between the course ID and the frequency of pauses for taking notes, see Fig. 4.3.

Using data analysis tools like Power Bi or Tableau is a quick way to get information to campus staff about the most popular videos and items. It might be interesting to compare this information with the number of students in each class. Also, it would be interesting to see the content the most viewed videos. Are they very interesting, are they very difficult, or are there a lot of students studying this subject.

Exponential function curve in Fig. 4.4 is used to depict the trend in which hour of the day students watch videos. There are videos that are watched throughout the day – during studies at the university and when studying at home, and there are those that are watched only a few times, maybe once during a lecture. University staff can gauge not only how requested or popular videos are, but also how busy and used servers are at different times of the day. So, the beneficiaries are not only the lecturers and the administration, but also the keepers of the infrastructure, both providing the service and planning the development.

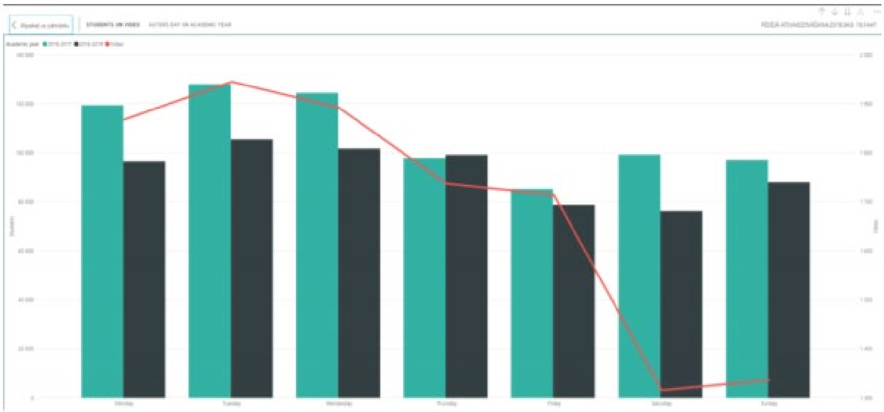

Fig. 4.2. Viewing of video lectures by day of the week.

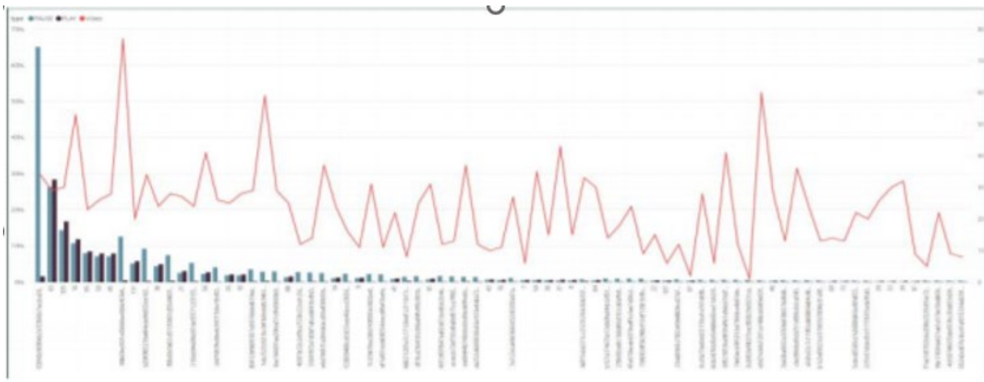

Fig. 4.3. Video pause rate versus video watch rate.

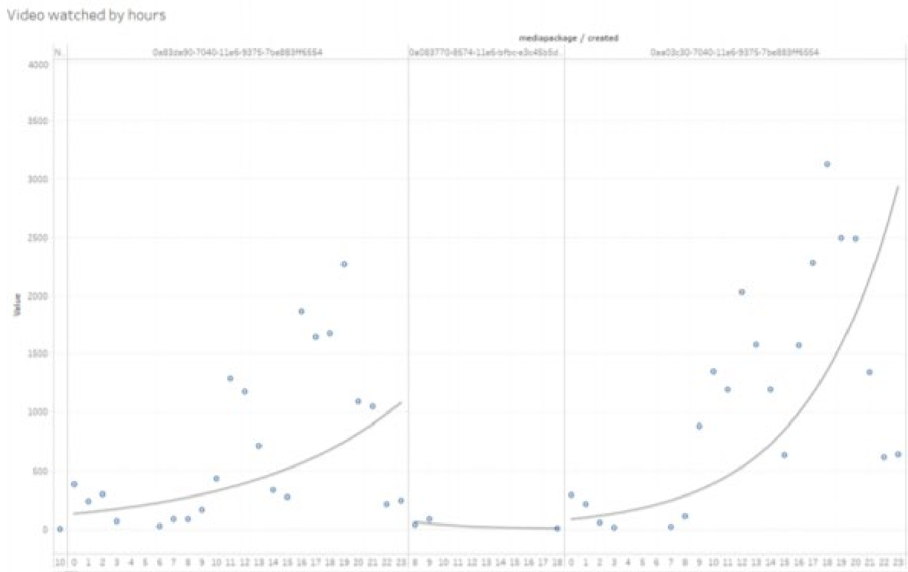

Fig. 4.4. Watching of video lectures by hours of the day.

Figure 4.5 provides a very interesting information about student activity – how many times each student has watched the videos.

Fig. 4.5. Number of video lectures watched by each user.

From this figure it can be seen that there are students who use the opportunity to watch video lectures very often and there are students who do not watch them at all. Of course, here too, we can draw conclusions about how popular videos lectures are in general, but in order to make concrete decisions, there should also be information about the attendance of the particular student and information about the courses that are viewed. It is not mandatory to watch video lectures in the particular university, however we can see that the demand from the students is huge.

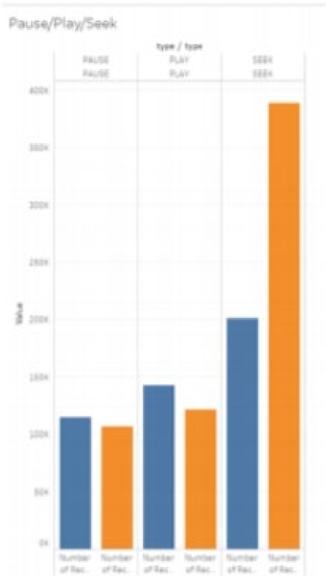

Fig. 4.6. Using of the Pause, Play and Search buttons.

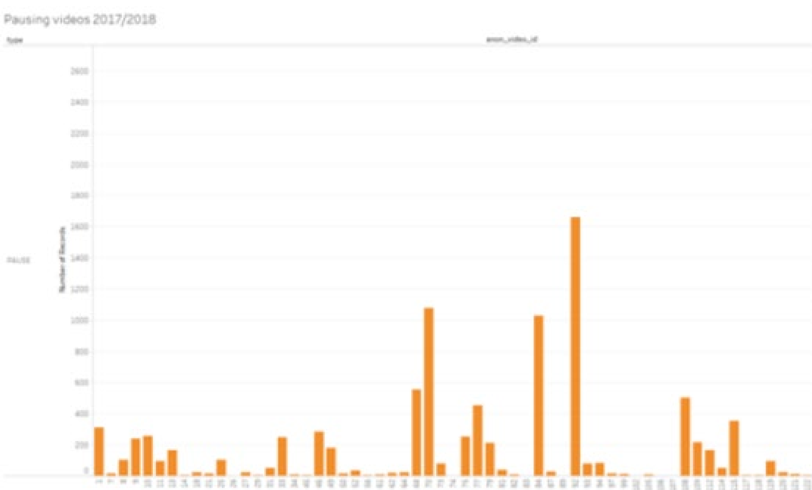

Fig. 4.7. How often each video lecture is paused.

In Fig. 4.6 the author has collected both data sources from both semesters and the actions performed when viewing the videos – play, pause and search – have been filtered. It can be seen that during the last semester, students have more actively used the search option while watching videos. The author thinks that this is because technology has developed in the two years between the two semesters, and the search gives a better result, and it is also good information for instructors – if they need to improve the keywords or bookmarks of the video. E-learning environment developers can draw conclusions whether the existing search engine is sufficiently developed (Alksne, 2019).

Conclusions

1. Viewing of video lectures at the Polytechnic University of Valencia was investigated in detail.
2. It is best to divide the video lectures into 5–10-minute videos because it improves the students' perception of the lectures.
3. Students search for videos most actively in the second semester, which can be explained by the rapid development of search tools.

5. Guidelines for creating a video lecture

This chapter presents the guidelines compiled by the author for creating video lectures and filming the corresponding teaching materials. The author has developed these guidelines based on a thorough analysis of the literature. Next, the entropy and syntactic information of the video lectures will be calculated and the impact of the guidelines on these informative characteristics will be analysed.

- Before starting video filming, you should try to follow the technical guidelines that recommend technical standards for filming, editing and installation.
- The technology used should not disturb or divert students' attention from the lecture.
- The video recording system used must also be able to manage larger volumes of video production.
- Videos must be adapted to such a format that they can be viewed on as many platforms as possible.
- Attention should be paid to the video production forma.;
- "Voice together with presentation" type of video lectures attract the most long-term attention.
- Video creators should try to film in an informal setting where the instructor can make good eye contact with the audience.
- Videos with a strongly planned course of presentation and the pace of changing elements are the most effective in studios.
- The colours of the layout should not be too diverse.
- Shorter videos are more engaging than longer ones.
- When creating training material, it should be noted that Khan-style training videos are more engaging than PowerPoint slides and/or code screenshots.
- When filming a video, the text should be written in clear handwriting and good drawing skills should be used.
- All shots must be clearly focused and well framed; zoom should only be used to focus attention, otherwise its use should be avoided.
- 160 words per minute is recommended as the optimal speech speed for presentations.
- Instructors should spend time planning before shooting the video. The planning stage has the biggest impact on the final result of the video.
- The content of full-class lectures should be divided into 5–10-minute long summary videos.
- All the material told and shown in the class should also be shown on video.

- Presentation of the introductory and content text of the course program should not be too long (Alksne, 2016).

6. Maximum syntactic information of a video lecture

Syntactic information is characterized by the relative increase in knowledge of its recipient. Syntactic information is the knowledge we receive from a generally noisy data channel. In 1953, Shannon investigated the question of quantifying syntactic information to analyse communication systems. Nowadays, in the 21st century, new types of data have emerged, such as biological data, web data, topographic maps and medical data, etc. Analysing the new data and discovering new knowledge about the new data has also resulted in new metrics for syntactic information (Angsheng Li and Yicheng Pan, 2016).

Information can be captured or transmitted as a variable that can have different values. Technically, we get information as a variable by looking at its value, just like we get information from an email when we look at its contents. Only in the variable case is the information the process behind it (Vajapeyam, 2014).

It is important to remember that Shannon's syntactic information in no way represents the quality or veracity of the information provided. Semantic information, which includes concepts such as thesaurus and dynamic entropy, serves this purpose. Shannon entropy is the average amount of information a message contains. Entropy is a quantity that depends only on the statistical nature of the source of the message, expressed as a probability (Carlson, 1986).

Different definitions of entropy are used to evaluate the informative content of videos. Entropy is a number that can be calculated for a randomly selected video lecture for a randomly selected time interval recorded in an audience and for the same length of time for a video lecture recorded following guidelines for creating a good video lecture that is easier for students to understand (Alksne, 2016).

Entropy is most often used to find specific locations in a video. For example, entropy is part of the *Hue* parameter in the HSV colour system to identify regions of the frame that will characterize a certain activity during a certain period. Entropy is a good way to represent the heterogeneity or unpredictability of a data set, and it depends on the context of the measurement (García-Rodríguez, 2013).

Also, an algorithm based on information entropy of the human skeleton has been developed, which is used to analyse information from RGBD video. The information entropy of the angles of the human skeleton is analysed, the value of which is significantly higher in abnormal videos than in normal videos. Much abnormal behaviour such as fights, robberies or similar chaos can be detected in this way (Luo, 2016).

Experimental results in studies show that the movement state of a panicked crowd has a higher entropy and a normal crowd state has a lower entropy. When riots break out, pedestrians often move in a hurry. Pedestrian movement depends on several attributes, such as age and gender. Also, the speed of movement of individuals differs. And the movement information of individual body parts (arms, torso and legs) is also different. The flow of motion in a crowd video represents a state of order or disorder (Xuguang Zhang, 2019).

A similar study was conducted on video aggregation of memory-based entropy. The authors predicted the memorability index and calculated the entropy value of the image. To create a summary of someone's video, the frame with the maximum memorability score and entropy value in each frame is selected.

In all these cases above, entropy searches for and highlights distinct video frames. The above authors have shown that it is not only possible to use entropy when the video is already taken, but also to influence the entropy while taking the video, following rules or guidelines that have already proven results when transmitting information to humans. As well as the aforementioned studies, the impact of video lectures on learning outcomes has been investigated (Weber, 1980).

The author has quantified the maximum syntactic information that can be provided by a face-to-face lecture of a certain length. If this lecture is filmed, the corresponding video lecture contains much less information due to the technical limitations of the receiving and transmitting video camera. Therefore, the author's assessment of the face-to-face lecture is the upper limit of the informative parameters of the video lecture.

As already mentioned, syntactic information refers only to the unexpected amount of data, not to its meaning. It is assumed that the instructor talks and shows slides and demonstrations for ten minutes (take ten minutes as an example). Thus, the audience has received a certain amount of optical and acoustic information through the eyes and ears. This is the maximum possible information. If the lecture is recorded on video with sound and later produced, the information presented in this video lecture will be reduced due to the technical limitations of the video recorder (limited optical and acoustic bandwidth, etc.). A lecture delivered by a natural instructor is considered a noisy communication channel consisting of a sound subchannel and a light subchannel. Each subchannel transmits frames for which the maximum Shannon entropies are calculated based on the human sensor-ear and eye-resolution of various parameters of the information-encoding signal. The frame rate is determined by the limiting properties of the human ear and eye. The maximum transmitted total amount of information in both subchannels and the entire channel is calculated, as well as the corresponding channel capacity.

Results:

The maximum entropy of the audio channel for a video lecture is (Alksne, 2022)

$$H_{\mathrm{s\,max}} = \log_2 2^{N_\mathrm{s}} = N_\mathrm{s}. \qquad (20)$$

Previously it was calculated that the number of cells in the channel N_s = 6583070, so $\boldsymbol{H_{\mathrm{s\,max}}}$ **= 6583070 bits.**

The maximum information in the length of the video lecture t = 600 s $\boldsymbol{Info_{\mathrm{s\,max}}}$ **= 3.95 × $\mathbf{10^{12}}$ bits.**

The maximum information throughput of a noiseless audio subchannel is

$$C_{\mathrm{s\,max}} = \frac{Info_{\mathrm{s\,max}}}{t} = \frac{H_{\mathrm{s\,max}}}{\Delta t_\mathrm{s}} \qquad (21)$$

Inserting the above $Info_{s\,max}$ and t or $H_{s\,max}$ and Δt_s values in Eq. (21), we get

$\boldsymbol{C_{s\,max} = 6.58 \times 10^9}$ **bits/s**

The maximum entropy of the light channel for a video lecture is:

$$H_{l\max} = \log_2 2^{N_l} = N_l, \tag{22}$$

thus $H_{l\,max} = 7.72 \times 10^9$ bits. (23)

The maximum information of the light channel

$$Info_{l\max} = \left[\frac{t}{\Delta t}\right] \cdot H_{l\max} \tag{24}$$

$$Info_{l\max} = \left[\frac{600}{5\times10^{-2}}\right] \times 5\times10^9 = 6.2\cdot10^{12} \text{ bits}$$

The maximum capacity of the light channel

$$C_{l\max} = \frac{Info_{l\max}}{t} = \frac{H_{l\max}}{\Delta t_l} \tag{25}$$

putting the values $Info_{l\,max}$ and t, or $H_{l\,max}$ and Δt_l into Eq. (25), we get

$C_{l\,max} \approx 1.54 \times 10^{11}$ bits.

6.1. Total maximum lecture information and lectures as a communication channel capacity

The obtained information characteristics of the sound and light subchannels allow us to find the maximum information and the maximum capacity of the entire lecture simply by summing the corresponding quantities, since we can assume that they are independent. In this way, the maximum information reached by the video lectures considered

$$Info_{max} = Info_{s\,max} + Info_{l\,max} \tag{26}$$

and the maximum information throughput of the entire lecture channel is

$$C_{max} = C_{s\,max} + C_{l\,max}\,, \tag{27}$$

because the amounts of information can be summed, but the information transmission time is the same for both subchannels. Inserting the corresponding quantities in Eqs (26) and (27), we obtain

$Info_{max} = (3.95 \times 10^{12} + 9.26 \times 10^{13})$ bits $\approx \boldsymbol{9.65 \times 10^{13}}$ **bits** , and

$C_{max} = (6.58 \times 10^9 + 1.54 \times 10^{11})$ bits/s $\approx \boldsymbol{1.61 \times 10^{11}}$ **bits.**

From these results, it is clear that the Shannon (syntactic) information characteristics of the entire lecture channel are almost completely determined by the light subchannel, since the information carried by the sound subchannel is smaller than more than one order of magnitude. The entropy ratio of light and sound frames is even higher:

$$\frac{H_{l\max}}{H_{s\max}} = \frac{7.72\times10^9}{6583070} \approx 1173$$

Thus, the contribution of the speaker's voice to the syntactic information is almost negligible. At first glance, this result seems to be expected, since sight occupies the highest place in the hierarchy of human senses. The lecture seems to require only a slide show. On the other hand, this is a paradoxical result, because practically we know that the role of the teacher is primary. This paradoxical result is a consequence of neglecting the sense of the lecture when computing syntactic Shannon information. Not only the voice, but also the lecturer's intonation and gestures play an important role in expressing the lecturer's attitude towards the content. It should also be noted that if the instructor were to use additional sound accompaniment, such as music, with a larger sound frequency bandwidth up to 20 kHz [the maximum bandwidth of the human ear (Nave, 2016)], then $H_{\text{s max}}$, $Info_{\text{s max}}$ and $C_{\text{s max}}$ would increase by more than an order of magnitude, reaching maximum possible values comparable to the corresponding light subchannel parameters. This is the situation at concerts.

We can compare the previously calculated information transmission capabilities of sound and light subchannels with the known information transmission capabilities of human hearing and vision. We have found that $C_{\text{s max}} = 6.58 \times 10^9$ bits/s and $C_{\text{l max}} = 1.54 \times 10^{11}$ bits/s, in contrast, the capacity of the human auditory channel is about 104 bits and the capacity of the human visual channel is about 107 bits, respectively, as estimated by Temnikov (Temnikov, 1971). Recent results for these human sensor channels are similar at about 105 bits and about 107 bits (Markowsky, 2017). Power values calculated by the author are 4–5 orders of magnitude higher.

How can such a large difference be explained? First, we have calculated the peak power values of the natural lecture, which serve as upper bounds for the sound and light subchannels. This means that all cells and all frames were equally reliable. In practice, this is not the case because the sensitivity of the ears and eyes is spectrally selective. For example, the human ear is most sensitive to sounds in the frequency range of 1500 to 4000 Hz, while the human eye is most sensitive to green-yellow light at a wavelength of 555 nm (5.4×10^{14} Hz) (Jehonovičs, 1984).

The content of the lecture can also affect the shot probabilities. We also did not take into account the presence of noise in both sound and light subchannels in our calculations. Finally, the transmission of perceived light and sound information in the nervous system and its processing in the brain is ignored. It is known that there is a huge amount of information compression going on there (Markowsky, 2017). Obviously, the optical and acoustic perception systems of humans cannot perceive all the information that is physically available.

Nevertheless, the results obtained for a natural lecture are overestimated. However, they can be used as upper bounds for the appropriate amounts of a video lecture, since the information characteristics will be much lower due to the technical limitations of the video camera.

The proposed method of calculating Shannon's information characteristics can be used not only for determining their maximum values, but also in the more general case of introducing cell probability distributions in all frames and also changing cell sizes. Appropriate variations of the probability distribution and cell sizes would allow the empirical conditions of an optimal lecture to be met. Thus, the characteristics of optimal lecture information could be calculated. Of course, in this case, a mathematical modification of the proposed approach is necessary (Alksne, 2016).

The method based on the continuous communication channel capacity Formula (13) proposed and used to calculate the maximum Shannon information characteristics of the natural lecture is not accurate. However, we believe that the method is logical and the approximations made do not significantly change the results. Further theoretical and experimental studies are needed to prove its practical applicability.

In principle, the proposed method is quite general. It can also be used to calculate syntactic optical and acoustic information characteristics of any world object, such as landscapes and streets with people, and space objects.

7. Characterization and analysis of video lectures

7.1. Characteristics of video lectures

Eleven different lectures were selected for analysis or entropy calculation. Lectures can be divided according to the way the lecture is filmed – in the auditorium, zoom, as well as whether it is edited or not.

Table 7.1

Video Sequence Number and Type of Video Lecture

Video No. 1	Video lecture by Zanda Rubene	Filmed in the auditorium, edited
Video No. 2	Video lecture by Juris Blūms	Filmed in the auditorium, unedited
Video No. 3	Kahn style video lecture – Yulia Maksimkina	Voiceover presentation
Video No. 4	Alexander Dolgitser's video lecture	Voiceover presentation
Video No. 5	Video lecture by Ingus Skadiņš	Filmed according to the script
Video No. 6	Video lecture by Ansis Jurģis Stabings	Filmed in the auditorium, edited
Video No. 7	Video training by Paula Freimane	Filmed according to the script
Video No. 8	Fragment of a physics experiment	Voiceover presentation
Video No. 9	Video lecture by Inta Volodko	Filmed in the auditorium, edited
Video No.10	Video lecture by Andris Ozols	Voiceover presentation
Video No. 11	Second video lecture by Zanda Rubene	Filmed in the auditorium, edited

7.2. Video lectures as code analysis

A natural lecture delivered by a lecturer is treated as a noiseless communication channel consisting of a sound subchannel and a light subchannel. Each subchannel transmits frames that are calculated by the Shannon entropy Formula (20):

$$H = \frac{\sum_{n=1}^{N} p(n)\log_2 p(n)}{\log_2 N}, \tag{28}$$

where p is distribution of probabilities by points (pixels); N is the total number of points in the division.

The entropy value H is normalized to obtain a relative measure that can be compared to video lectures. $\log_2 N$ in formula (28) denotes the maximum entropy.

Three different entropies are calculated for each video lecture:

a) video frame entropy (video entropy);

b) audio signal intensity entropy (audio time entropy);

c) audio spectral entropy (audio spectral entropy).

Since video lectures have slow-moving scenes, the entropy is not calculated for each frame but for a smaller number of randomly selected frames. The author assumes that these shots capture enough information to describe the entire lecture. Audio frames/samples are selected in the same way. Finally, the average entropy level is obtained, which is

$$H = \frac{\sum_{m=1}^{M} H(m)}{M}, \tag{29}$$

where M is the number of video or audio frames.

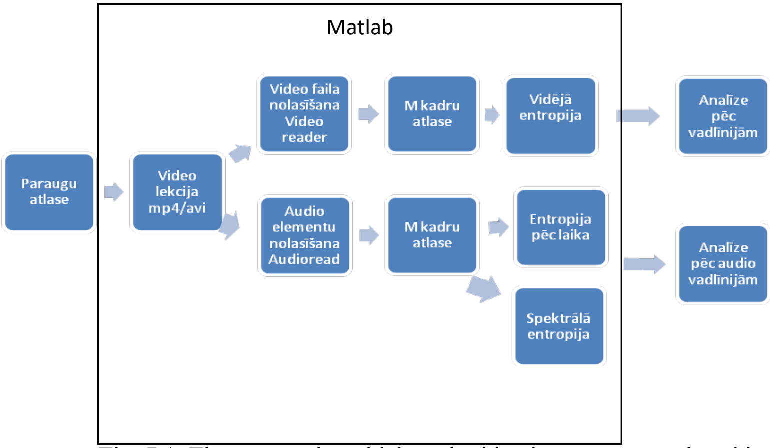

Fig. 7.1. The process by which each video lecture was analysed in Matlab.

Figure 7.2 shows how the video lecture analysis looks like in the Matlab program.

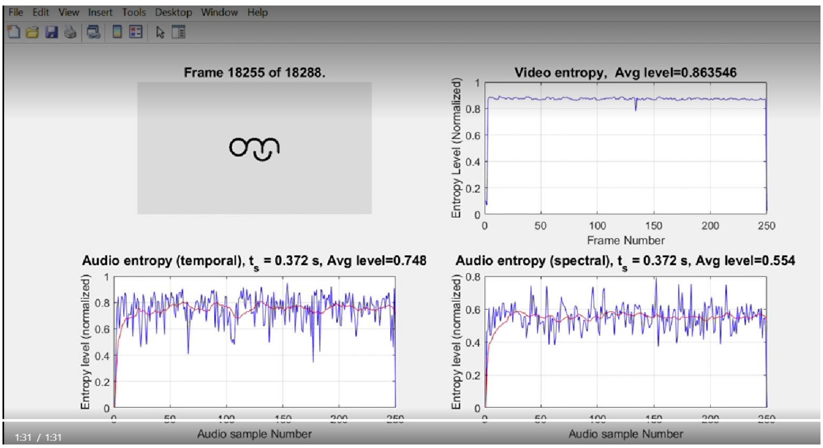

Fig. 7.2. The entropy results of Z. Rubene's video lecture analysis.

All the obtained entropy results and compliance of the video lectures with the guidelines are shown in Table 7.2. Taking into account that, the guidelines were created for the filming of high-quality lectures; the author believes that the quality of a video lecture depends on the number of guidelines published in the scientific literature.

Table 7.2

Number of Guidelines Followed

	Video sequence number									
	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	No. 9	No. 10
Voiceover presentation	No	Yes	Yes	Yes	No	No	No	No	Yes	No
Good eye contact	Yes	No	No	No	Yes	No	No	No	Yes	No
Strong presentation, variable pace	No	Yes	Yes	No	No	No	-	No	Yes	No
Not too many colours	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No
Kahn-style video lecture	No	No	Yes	No	No	No	No	No	No	No
Clear handwriting and drawings	-	-	Yes	No	Yes	-	-	Yes	-	-
100 words per minute	99	117	94	40	76	146	-	55	104	116
Good lighting	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Clearly focused and well framed	Yes	Yes	Jā	No	Yes	Yes	Yes	Yes	Yes	Yes
Avoid zooming	Yes	No	Yes	No	Yes	Yes	No	No	Yes	Yes
Still camera	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clear speech	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Minimal noise	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Default background	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
Smooth effects	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes
Processed video	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	No
Background audio balance	-	-	-	-	-	-	Yes	-	-	-
Introductory material	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes	No

Table 7.2 continued

Recorded in the studio	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Lecturer's voice male/female	woman	man	woman	man	man	man	music	woman	woman	Man
Total entropy	1.6115	1.845	1.2384	1.4601	1.5592	1.6498	1.7219	1.1993	1.4019	1.1837
"Yes" result in the video	5	4	9	2	7	4	5	6	8	5
"Yes" result for sound	4	2	4	0	3	3	4	3	5	2
Overall score	9	6	13	2	10	7	9	9	13	7

Table 7.3

Video Sequence Number

	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	No. 9	No. 10
Average video entropy, in relative units	Video No 1 0.8635 Video No. 11 0.8516	0.8625	0.4794	0.6691	0.7492	0.9028	0.8289	0.7403	0.6589	0.4067
Average temporal audio entropy, in relative units	Video No. 1 0.748 Video No. 11 0.754	0.822	0.759	0.791	0.810	0.747	0.893	0.459	0.743	0.777
Average spectral audio entropy, in relative units	Video No. 1 0.554 Video No. 11 0.559	0.554	0.518	0.610	0.512	0.543	0.460	0.506	0.520	0.452

Figure 7.3 shows the dependence of the average video entropy on the number of guidelines. We can see that the more guidelines covered, the lower the entropy.

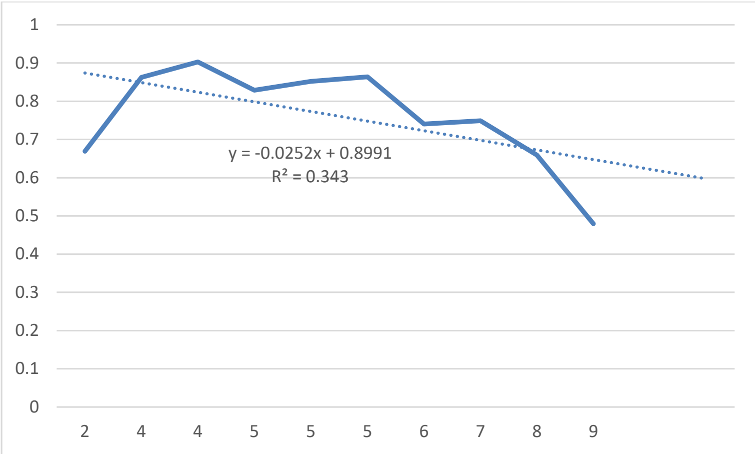

Fig. 7.3. Dependence of the average video entropy on the number of followed guidelines (result of the number of "Yes").

Roughly, it can be assumed that the correlation between the average video entropy and the number of guidelines can be described by a linear regression equation. It is determined by the method of least squares. The equation and the regression line are shown in Fig. 7.3.

To verify the closeness of the found relationship between the number of guidelines in a video lecture and the average video entropy, the Pearson correlation coefficient is used:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})\cdot(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\cdot\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}, \tag{30}$$

where:

x_i – feature variant (in our case, the number of fulfilled guidelines, or the number of "yes");

y_i – a variant of the resulting feature (in our case, entropy values);

$\overline{x}$ – the arithmetic mean of the feature;

$\overline{y}$ – the arithmetic mean of the resulting feature;

n – the number of pairs of variants, or the size of the sample set (in our case, the number of types of video lectures considered n = 10). The author uses the MS Excel function to calculate the correlation coefficient according to Formula (30). The Pearson coefficient is

$$r = -0.59546.$$

The correlation coefficient is negative because the regression line is downward sloping. Its modulus corresponds to a moderately close linear correlation between average entropy and the number of guidelines. Considering that the actual relationship in Fig. 7.3 is more complicated than linear, the result should be considered good.

The reliability of the resulting Pearson's correlation coefficient α can be found from the size of the Student's distribution (expressed in terms of gamma functions):

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}. \quad (31)$$

This was used in the MS Excel function for r calculation as well. MS Excel has a function also for probability of error in the calculation of the Pearson correlation coefficient

$$p = 1 - \alpha \text{ (328).}$$

Using it, the author has found $p = 0.069323 \approx 0.0693$ and probability of reliability or its reliability, $\alpha = 0.931$. So, the negative correlation of video lecture entropy with the number of guidelines can be considered proven.

Continuing the analysis of the video lectures, it should be noted that there are also exceptions, in this case Video No. 4. As we can see, the video lecture receives only two "YES" because although there are two screens, there are also large black parts of the screen that do not change throughout the video, so the entropy of this video is low.

To draw some conclusions about sound entropy, let us look at Table 7.2. It shows that where the lecturers are women, the average time audio entropy is lower. A possible cause could be that female lecturers speak in a more monotonous voice than male lecturers. The author has counted the words in the first minute of the experiment because one of the guidelines mentions the optimal number of words per minute to get a rough description of the speaker. This cannot be used to draw conclusions about the whole lecture because, for example, from lectures No. 4 and No. 5 we see that the teacher speaks more slowly when drawing and faster when speaking to the camera. We can also see it in Video No. 8, where the audio entropy is really low because the woman speaks in a slow tempo throughout the video.

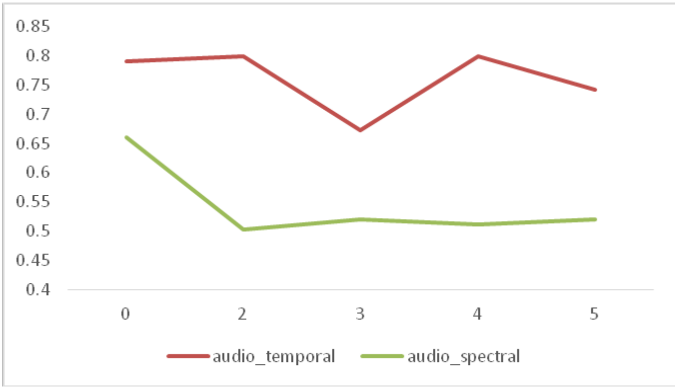

Fig. 7.4. Dependence of average audio entropies on number of followed guidelines (“Yes” count result).

From Fig. 7.4, where average entropy vs number of “YES” (audio compliance guidelines), we can see that there is no significant correlation between compliance with audio guidelines and spectral and temporal entropy of audio, but spectral and temporal entropy analysis of each video lecture gives us a great benefit because we can make conclusions about the influence of the speaker/teacher's voice and speech on entropy. The smoother the speech, the lower the average entropy and the easier the speech is to understand (Chen, 2015).

Looking at the average entropy against the number of “YES” (guidelines for audio) it can be seen that there is not significant correlation between the mach for audio guidelines and audio spectral and temporal entropy (Fig. 7.4), although the analysis of each video lectures spectral and temporal audio entropy gives a lot of information because it is possible to make conclusions about the impact of the voice and speach of the speaker/teacher on the entropy. As the speach is smoother, the average entropy is lower and speach is easier to percieve.

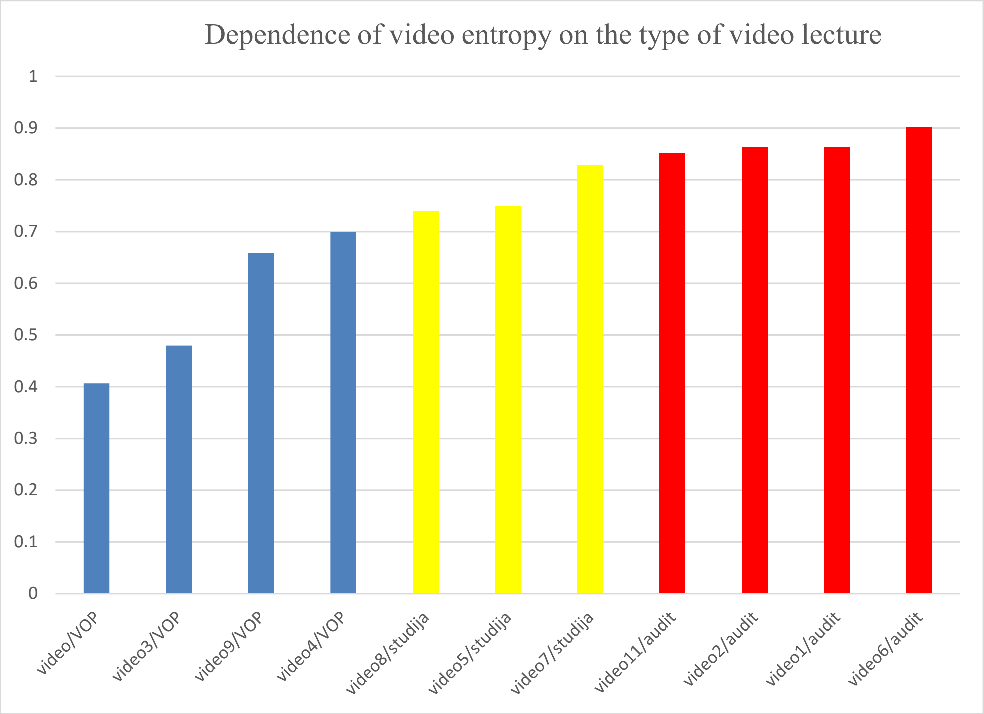

Fig. 7.5. Dependence of video entropy on the type of video lecture

Figure 7.5. shows that the entropy of a video lecture depends on its type, with the lowest entropy, which also proves one of the guidelines, is voiceover presentation (VOP). This group contains both Zoom videos and videos where you can see the instructor with the presentation. In the middle, marked yellow, are those video lectures filmed according to the script and edited footage, without an audience. All lectures filmed in the auditorium have the highest entropy. From this, we can conclude that a student, watching a video lecture consisting of a presentation and the teacher's voice, will be able to understand the video much more easily than the video lectures filmed with the audience.

There are video lecture parameters that the instructor or the creator of the video lecture can change to affect the entropy both through their behaviour and through technical parameters. Some parameters need to be tested to demonstrate their effect on entropy by changing just one parameter in the video, for example, if there are no changes in the video, but the instructor only changes his speaking speed – he speaks faster or louder.

The main conclusion of this PhD thesis is that there is a correlation between the lecture type and entropy. Kahn-style video lectures with voice presentation have the lowest entropy, and studies have also shown that these lectures are easier for students to understand (Chen, 2015).

Of course, this type of lecture cannot be used in all situations and it should not be done, the instructor can make the right decision when necessary based on the knowledge of the type of video lecture and entropy.

Conclusions

After the analysis of average audio and video entropy values for 11 different video lectures using Matlab and comparing results the author can make the following conclusions:

1. Voiceover presentation and Khan style video lectures have the lowest entropy and it has been also proved that these lectures are easier to percieve for students (Chen, 2015).
2. For students, video lectures that consist of the presentation and the voice of the teacher are easier to perceive than the lectures captured in the classroom.
3. Video with zoom effects, variable focus of the camera and smooth effects are changing the value of the entropy.
4. Video lectures that are captured in the studio and edited have the lower entropy.
5. Lectures that are captured with good light where the changes of brightness and colours of the background are not too different have lower value of entropy.
6. If the speaker talks slower – changes of the audio entropy are higher.
7. If the speaker talks slower – average value of the entropy is lower.
8. Video lectures with voice of women have lower audio entropy.
9. Video lectures with an introduction screen/frame also have lower video entropy.
10. Audio entropy gets higher if the speaker during the video starts to raise the voice and speaks faster.

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