Towards Providing Relevant Digital Signage Advertisement to a Group of Users Based on Users' Interests Investigation

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***Abstract*—Nowadays an advertisement becomes more and more personal. Usually, internet data mining algorithms collect information about user's activities, analyze it and offer the most relevant context advertisement. But it is much more complicated to find information to show to a group of viewers in public places. This happens due to privacy restrictions and lack of algorithms that would allow finding mutual interests for a group of users. In this article, an approach to solving these problems through analysis of multiple visual viewers' characteristics is proposed.**

I. Introduction

Digital signage is designed to provide advertisements on large screens for undefined groups of people. Digital signage systems can be found in schools and universities, cafes and malls, research laboratories and government agencies. There are exist systems that do not allow a user to make any decisions about the content, and interactive systems a user can interact with [1].

The goals of the digital signage systems, their locations, and target audiences are vital parameters for designing the logic of selecting the relevant information to be shown. Personalization is currently one of the critical factors of a successful advertisement. As a result, it is necessary to have an algorithm that could provide a viewer with relevant information. In order to develop one, an investigation of the viewer's preferences should take place. It is not much of a leap to discover user's interests based on his or her personal data (e.g., search queries, locations, contacts) [2]. However, according to laws (for example, 152 Federal Law [3] in Russia and GDPR [4] in Europe), it is only possible if the person gives his or her signed agreement for personal data collection and proceeding. Since digital signage is aimed at unspecified groups of people, it is hard if not impossible to collect signed agreements in public places, and the organization owning the digital signage system has to work with anonymous data. It leads to the complexity of the interests evaluations. Moreover, it is a sophisticated problem to find a subject that is commonly interesting for several simultaneous viewers with interests as wide as poles apart.

The paper is structured as follows. Descriptions of existing solutions can be found in Section 2. The proposed concept of the digital signage control system and underlying technologies are described in Section 3. Section 4 provides the results of the experiment conducted to evaluate the suitability of technologies chosen in the third chapter.

II. Review of the Existing Solutions

There are several steps that have to be taken in order to provide personalized information using digital signage.

A. *Person recognition*

First of all, the audience the advertisement will be shown to should be analyzed. There could be one or several users standing by the screen, or the visible area might be empty.

If there are persons near the digital signage, the system shall collect information about them. Usually, this information contains age and gender. As a result, all viewers can be divided into several demographical groups, for example, male young, male adult, male old, female young, female adult, and female old viewers.

If the area is empty, the system can try to predict who will come by the screen in the next moment. Based on collected statistics the system can predict the demographical group of the person who is most likely going to pass by the screen in the next moment [5].

B. *Interests evaluation*

As soon as the audience is defined, the system evaluates their group interests.

The main assumption at this step is that members of one demographical group would generally have similar interests [6]. The system keeps information about the interest value each demographical group has for each subject. It is obvious that such an approach has a cold start problem: it is complicated to understand whether the new subject will be interesting for a group of users and vice versa.

There are several machine learning methods that can be used for model training. The most popular of them include [5], [7]:

- Decision Tree;
- Association Rule;

- Naïve Bayes;
- Logistic Regression.

After personal interests are evaluated, the system faces the problem of mutual interests' evaluation. The commonly used way to solve this problem is to choose a primary demographical group. This decision is made on the audience interests' analysis. As a result, digital signage suggests the most popular subject for the primary demographical group. But in this case, shown information would have no impact on viewers who belong to other demographical groups.

C. Collation of information

After the subject chosen, digital signage provides a relevant advertisement. At this step, the context (e.g., day of week, time of the day, and weather) can be taken into account [6].

D. Result estimation

After a group of viewers saw an advertisement, the results shall be estimated. It is essential to find out whether a group of users paid attention to the information on the screen. If so, an assumption can be made that viewers were interested in the advertisement. If the viewers just took a glance on the screen or completely ignored it, it means that the subject left them cold. In this case, it is expected that the subject was chosen wrongly and the model shall be re-trained. Also, the model can be re-trained by some schedule.

The amount of time a viewer belonging to a demographical group was watching an advertisement is useful for updating the information about the interests of the demographical group.

III. Concept of a Digital Signage system

To provide information to a group of users more carefully, the following concept is proposed. This concept urged to eliminate some of the disadvantages of the existing solutions.

The viewers are divided into demographical groups, and it is still supposed that people belonging to one demographical group have similar interests. However, to evaluate the interests with a higher precision, several improvements in the dividing process are suggested. Also, correlations between a person's emotions and advertisement effectiveness are supposed to exist. For example, in charity advertising emotions works extremely good for increasing donations [8].

Moreover, the proposed approach applies an ontology of the subjects [9]. This approach will be used in evaluation of interests for subjects not seen before.

For evaluation viewers' age, gender, emotions and the time a viewer is looking at the screen, the proposed digital signage system has a camera and Microsoft Azure Face API [10] is used for image processing.

A. Person representation in the digital signage system

Nowadays, it is possible to anonymously collect not only information about age and gender but also to evaluate the probability of a particular emotion reflected on the person's face. For example, Microsoft Azure Face API provides an ability to estimate the probability of one of the following emotions from a photo:

- Anger;
- Contempt;
- Disgust;
- Fear;
- Happiness;
- Neutral;
- Sadness;
- Surprise.

Based on these probabilities all viewers can be divided into a larger number of more slender demographical groups. Also, one can elaborate on the viewer's age. For example, instead of dividing users into young, adult and old the system can assign a viewer to a group of members with disproportion in age no more than ten years.

All these improvements would allow grouping viewers more accurately. There will be fewer differences between persons belonging to one demographical group. As a result, the system could provide more relevant information to the viewers.

B. Advertisement representation in the digital signage system

To provide information more carefully the system shall keep the following information about each advertisement:

- List of subjects the advertisement represents, with the information about each subject's contribution.
- Advertisement duration.
- Information about views.
- The emotional effect of the advertisement represented as emotions' values changes caused by the advertisement watching by a person belonging to a demographical group.

C. Interests evaluation

The task of interest evaluation is divided into two subtasks: personal and group interest evaluation.

1) Personal interest evaluation

There are two categories of subjects presented in the subject ontology:

- Subjects, for which there is information about an interest of a particular demographical group.
- Subjects never demonstrated to any member of a particular demographical group.

a) Interests evaluation for known subjects

An interest of a demographic group in a subject can be evaluated. The following way to calculate the interest value is suggested:

1) Find all advertisements corresponding to subject i.
2) For a demographical group g find all viewers who saw an advertisement found in the previous step.
3) For each advertisement k calculate an average percent of time viewers were watching this advertisement.
4) Calculate an average value for each advertisement representing the subject.

The result can be calculated using formula (1):

$$subject_{i,g} = \frac{\sum_{a=0}^{n} \frac{\sum_{p=0}^{m} \frac{t_{view_{a,p}}}{t_{ad_a}} \times 100}{m}}{n} \quad (1)$$

Where $subject_{i,g}$ – subject i evaluation for a demographical group g; $t_{view_{a,p}}$ – time in seconds person p belonging to demographical group g was watching advertisement a; t_{ad_a}- duration of advertisement a; m – total number of viewers belonging to demographical group g, who saw advertisement a; n – total number of advertisements corresponding to subject i.

As a result, it is possible to calculate interest values for subjects that were seen by the members of the particular demographical group. This value is in the range between 0 and 100.

b) Interests evaluation for unknown subjects

It was shown how interest values can be calculated for subjects the members of the particular demographical group saw. But there can also be subjects unknown to demographical group members. To evaluate the interest of these subjects an ontology can be used. The ontology in a form of a weighted oriented graph is purposed for use.

There are the following assumptions for arcs between parent and child concepts:

1) Distance from parent to child concepts equals 0.

$$interest_l = \frac{\sum_{c=0}^{k} subject_c}{k} \quad (4)$$

2) Distance from child to parent concepts is more than 0 but less than 1.
3) The value is the same for each parent-child relationship.

Also, there are other relationships between concepts. To begin with, the distance between every two concepts not related with parent-child relationship is considered to be the same. This distance shall be more than the distance between child and parent concepts but less than 1.

Based on the distance weights the distance between every two concepts in the ontology can be calculated. It is not required to perform all these calculations each time a user walks by the screen. The system can keep calculated distance values until any changes in ontology occur.

Based on known interests' values and calculated distances between concepts, the system can calculate interest values for unknown subjects. In order to do this, the system shall find the closest known interest in a subject the value will be calculated for. If there are several known interests on the same distance from the selected unknown subject, the system shall choose the one that gives the biggest interest value. To calculate the unknown interest value the formula (2) can be used.

Where $subject_{i,g}$ – subject i evaluation for a demographical group g; $known\_subject_{j,g}$ – interest value of a closest known subject j for a demographical group g; $d_{i,j}$ –

$$subject_{i,g} = \frac{known\_subject_{j,g}}{\left(1 + d_{i,j}\right)} \quad (2)$$

the distance between concepts i and j in the ontology.

It is not necessary to calculate the values for all concepts in the ontology but only for the subjects of the advertisements in the system.

Such an approach provides the ability to calculate values for subjects the viewers have never seen before.

2) Interests evaluation for a group of users

If there is a group of viewers standing by the screen, the system can evaluate their interests by summing up the interest values for each user using formula (3).

$$subject_i = \frac{\sum_{b=0}^{v} subject_{i,\,g_b}}{v} \quad (3)$$

Where $subject_i$ – subject i evaluation; $subject_{i,\,g_b}$ - subject i evaluation for a demographical group g the viewer b belongs to; v – a number of viewers by the screen.

3) Advertisement interest evaluation for a group of users

An advertisement can correspond to several subjects. To calculate an advertisement interest value, an average of advertisement interests shall be counted using formula (4).

Where $interest_l$ – advertisement l interest evaluation; $subject_c$ – interest value for a subject c advertisement l corresponds to; k – total number of subjects presented in advertisement l.

The system can keep information about the contribution each subject has in each advertisement to provide an advertisement more accurate. This contribution has to be in a range between 0 and 1. The advertisement interest value can be calculated using formula (5).

$$interest_l = \sum_{c=0}^{k} subject_c * w_c \quad (5)$$

Where $interest_l$ – advertisement l interest evaluation; $subject_c$ – interest value for a subject c advertisement l corresponds to; w_c - $subject_c$ contribution in an advertisement; k – Total number of subjects presented in advertisement l.

As a result, the list of advertisements can be ranked based on this advertisement interest evaluation.

D. Emotions evaluation

For each demographical group we will try to find target emotions level. This level will be presented as list of target values for each emotion.

Also, the system shall keep information about the emotional effect each advertisement has.

1) Expected emotions evaluation

The system has to calculate emotional respond expected from a person belonging to some demographical group. To do it, the system has to calculate average expected emotions by the formula (6).

$$expected\_emotions_{c,g,l} = \frac{\sum_{p=0}^{m} emotion_{c,p,l}}{m} \quad (6)$$

Where $expected\_emotions_{c,g,l}$ - emotion c value person belong to demographical group g will have after advertisement l showing; $emotion_{c,p,l}$ - emotion c value person p belongs to demographical group g had, after advertisement l showing; m – total number of viewer belonging to demographical group g, who saw advertisement l.

For a cold start, formula (7) can be used.

$$expected\_emotions_{c,g,l} = target\_emotion_{c,g} \quad (7)$$

Where $target\_emotion_{c,g}$ – target emotion value for emotion c for a demographical group g person belongs to.

2) Personal emotions evaluation

Emotional result for each person can be calculated as changes in the difference between person's emotions and target values.

Personal emotional value can be calculated using formula (8).

$$emotion_l = \sum_{c=0}^{k} \left(\left| target\_emotion_{c,g} - real\_emotion_{c,p} \right| - \left| target\_emotion_{c,g} - expected\_emotions_{c,p,l} \right| \right) * \frac{100}{k} \quad (8)$$

Where $emotion_l$ – emotional gain of an advertisement l showing for a particular person; $target\_emotion_{c,g}$ – target emotion value for emotion c for a demographical group g person p belongs to; $real\_emotion_{c,p}$ – emotion c value person p has before the advertisement l was shown; $expected\_emotions_{c,p,l}$ - emotion c value person p will have after the advertisement l is shown; k – number of emotions taken into account.

3) Emotions evaluation for a group of users

The system can calculate an emotional gain as an approximate value for all users standing by the screen using the formula (9).

$$emotional\_gain_l = \frac{\sum_{p=0}^{k} emotion_{l,p}}{k} \quad (9)$$

Where $emotional\_gain_l$ – an emotional gain of an advertisement l showing for a particular group of viewers; $emotion_{l,p}$ – an emotional gain of advertisement l showing for person p; k – a number of persons standing by the screen.

E. Advertisement evaluation

The system has to sum up advertisement interest value, its emotional gain and context effect for each advertisement to choose an advertisement to be shown to a group of people by the screen (10).

$$advertisement_l = interest_l + emotional\_gain_l + context_l \quad (10)$$

Where $advertisement_l$– advertisement l evaluation; $interest_l$ – advertisement l interest evaluation; $emotional\_gain_l$ – an emotional gain of an advertisement l showing for a particular group of viewers; $context_l$ – advertisement l context evaluation.

The frequency of a particular advertisement demonstration and environmental effects can be taken into account as an advertisement context evaluation. To determinate the effect, each part of the advertisement evaluation has additional multipliers. In this case formula (10) turns into (11):

$$advertisement_l = x * interest_l + y * emotional\_gain_l + z * context_l \quad (11)$$

Where $advertisement_l$– advertisement l evaluation; $x -$ interest contribution in advertisement l evaluation; $interest_l$ – advertisement l interest evaluation; y – emotional contribution in advertisement l evaluation; $emotional\_gain_l$ – emotional gain of an advertisement l showing for a particular group of viewers; $z -$ context contribution in advertisement l evaluation; $context_l$ – advertisement l context evaluation.

Based on $advertisement_l$ value the system can rank advertisements and select the top one(s) to show for a group of users.

IV. EXPERIMENT RESULTS

It was decided to run an experiment to investigate the suitability of Microsoft Azure Face API. 18 persons took part in this experiment: 12 men from 23 to 42 years old and 6 women from 27 to 56 years old.

In this experiment did not consider any particular brands and products, and it was designed as short as possible.

For each tester there was the following scenario:

1) Tester was asked about his or her age and gender.

2) Tester was given the following short story:

"You are interested in some kind of a product. There are some vendors producing and selling this product. All products of this kind have the same characteristics and cost. You can buy as many products as you want. The following pictures are advertisements of these products. Please, evaluate from 0 to 10 the probability you will buy this product."

3) Tester was given 10 short animations (Fig. 1) in a random order. He or she had to look at each animation for 5 seconds. After this, he or she had to evaluate the probability he or she would buy the product. During the animations watching period, 10 shots per second were taken and sent to Microsoft Azure Face API (Fig. 2).

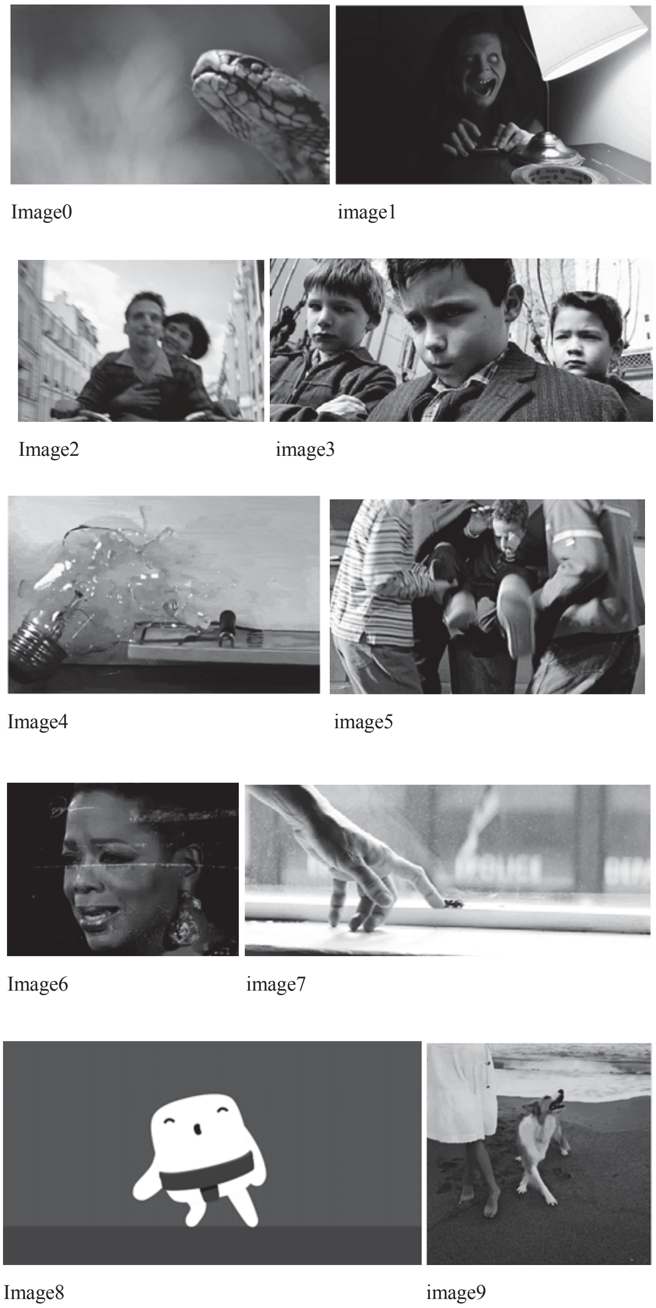

Fig. 1. Snapshots of animations shown during the experiment

Fig. 2. Examples of photos of a tester with different emotions

To start with, Microsoft Azure Face API accuracy in age and gender evaluation investigation took place. It turned out that Microsoft Azure Face API recognizes a person's gender with 100% accuracy and it makes mistakes in age evaluation no more than 4 years.

As the second part of elaboration, it was required to find out whether it is possible to awake emotions and place emotion changing on the record. To do this, it was assumed that each animation would awake certain emotions. Correlations between animations and emotions are presented in Table I.

TABLE I. ANIMATION DESCRIPTIONS AND EXPECTED EMOTIONS

Animation ID	Description	Expected emotions
image0	A snake spitting poison.	Disgust, fear.
image1	A monster suddenly turning off the light.	Surprise, fear, disgust
image2	A happy couple riding a motorbike.	Happiness
image3	Funny anger schoolboy.	Happiness, neutral
image4	A breaking lightbulb.	Neutral
image5	A group of schoolboys putting a boy into a rubbish-bin.	Anger, sadness
image6	Crying woman.	Sadness
image7	A woman helping a bug to roll over.	Neutral
image8	Smiling and dancing cartoon character.	Happiness
image9	A woman dancing with the dog on the beach.	Happiness

Microsoft Azure Face API identifies probabilities of particular emotions with high accuracy. Neutral was the dominant emotions on almost every shot taken during the experiment. To evaluate the emotional effect each animation has, minimum, maximum and average emotional values, the difference between minimum and maximum values, and between emotions on the first and last shots taken during an animation watching were collected. Usually, this difference was very small. In this part of elaboration, only the difference between emotions at the beginning and at the end of the animation's showing was taken into account. The results are presented in Table II.

TABLE II. EMOTIONS CHANGING

Animation ID	Description of emotions changing	Expected emotions
image0	Over 73% of testers seemed to become less neutral. 3 of the testers expressed a little increase in anger, fear, and disgust.	Disgust, fear.
image1	Over 67% of testers seemed to become less neutral. Over 44% showed increasing happiness level. 2 of testers seemed to be a little surprised. 27% showed growth of contempt and for 33% contempt expression was decreased.	Surprise, fear, disgust
image2	Over 39% of testers seemed to become less sad and 33% became happier. Over 56% became less neutral. 2 of the testers showed anger decreasing and 1 tester showed disgust decreasing.	Happiness
image3	44% of the testers seemed to become less neutral. However, the other 44% at the end of the picture showing seemed to become more neutral. Over 28% became happier and less sad.	Happiness, neutral
image4	44% of the testers seemed to become more neutral.	Neutral
image5	39% of the testers seemed to become less neutral and less happy.28% became sadder, 1 of the testers seemed to become a bit angry.	Anger, sadness
image6	50% of testers seemed to become sadder. Also, 50% became less happy.	Sadness
image7	50% of testers showed increasing in neutral level. 39% became less happy.	Neutral
image8	33% demonstrated happiness increasing and 38% - sadness decreasing.	Happiness
image9	50% of testers seemed to become happier. Also, 28% became less sad	Happiness

Apparently, not all of the animations hit emotional goals. It is assumed that this could happen due to the short animation length and inability to abstract the tester from the destruction factors. However, it was found out the Microsoft Azure Face API can evaluate emotions quite accurately.

As a final part of the experiment, an effort to predict correlations between emotions and product attraction was done. For this purpose, the animations scores were normalized. For result analysis Microsoft Machine Learning Studio was used [11]. Sadly, dependence with sufficient accuracy was not identified, but it turned out that the difference between minimum and maximum of neutral and happiness influence the scores the most.

As feedback, testers suggested using longer animations and showing an advertisement for a particular kind of product since it was difficult to associate the animation with the "abstract product". Also, they claimed that the emotions experienced during the watching of the previous animation affected emotions awaken by the current animation.

V. CONCLUSION

In this article, an analysis of main pain points of providing personalized advertisement through digital signage to a group of users has been done. To solve this problem, a concept of the system was suggested that shall take into account not only the context and interests of an average member of a particular demographical group but also considers the emotional effect provided by the advertisement. Also, a theoretical way to find mutual interests for a group of users was proposed.

To check the appropriateness of the selected technical tools an experiment was carried out. The results of this experiment showed that selected technical tools provide suitable accuracy in calculating the requested data. However, correlations between emotions and product attractiveness have not been found.

Looking forward it is planned to run additional experiments taking into account feedback from testers. This information will help to prove or reject the hypothesis that emotions affection on a person's face can be used to choose an appropriate advertisement more accurate.

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