Realizing Targeted Advertising in Digital Signage with AVA and Data Mining

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***Abstract*—How to realize targeted advertising in digital signage is an interesting question. This paper proposed an Intelligent Advertising Framework (IAF), which pioneers the integration of Anonymous Video Analytics (AVA) and Data Mining technologies to achieve Targeted and interactive Advertising. By correlating AVA viewership information with point-of-sale (POS) data, IAF can be used to establish a link between the response time to an ad by a certain demographic group and the effect on the sale of the advertised product, so as to provide customers/advertisers with intelligence to show the right ads to right audience at right time and in the location.**

***Index Terms*—Targeted Advertising, Digital Signage, Anonymous Video Analytics, Data Mining, Intelligent Advertising Framework**

I. Introduction

DIGITAL signage (DS) [1,2] is the term that is often used to describe the use of LCD, LED, plasma, or projected displays to show news, ads, local announcements, and other multimedia content in public venues such as restaurants or malls. In recent years, the digital signage industry has experienced tremendous growth, and it is now only second to the Internet in terms of annual advertising revenue growth [3].

Targeted advertising is a type of advertising whereby advertisements are placed so as to reach consumers based on various traits such as demographics, purchase history, or observed behavior [4]. On one hand, targeted advertising helps to identify potential customers, create a real-time relationship with these customers, improves their experience, and provides them cross-sell services to boost incremental revenue. On the other hand, it helps to reduce waste and improve advertisers' Return on Investment (ROI) by just placing advertisement to the potential purchasers rather than the whole population.

Targeted advertising has been adopted in many industries, including banking, insurance, telecom marketing [5,6]. But targeted advertising is still a new concept for digital signage industry. How to realize targeted advertising in digital signage is an interesting question. That requires the digital signs have the capability to dynamically select and play advertisements according to the traits of the audiences in front of them, rather than select and play in a predefined or random order. Future audience belonging to the same demographic as previous audience will be targeted based on the viewing behavior of the previous audience.

This paper proposed an Intelligent Advertising Framework (IAF), which integrates Anonymous Video Analytics (AVA) and Data Mining technologies to achieve Targeted and interactive Advertising. It uses AVA to capture human faces and recognize demographic information of the audiences, then correlate this information with ads playing list, point-of-sale (POS) data as well as other context information, such as time, location, weather etc., and use data mining algorithms to learn advertising models based on the correlation. Using these models, IAF is able to intelligently select and play the most appropriate ads to the audience in real time. IAF realized an architecture with combination of cloud based data mining and client based real time targeting.

The other sections in this paper are organized as follows. Section 2 illustrates the IAF architecture and the components therein. Section 3 and Section4 describe AVA technology and data mining algorithms respectively. Section 5 describes the process for targeted advertising. Section 6 concludes the paper.

II. IAF Architecture

Fig. 1 demonstrates an end to end architecture of IAF. Some components, including Analytic Server, Data Mining Server, Data Mining Module (DMM) and Content Management System (CMS) will run in the Cloud. Other components, AIM Suite and Digital Player will run on the Client, i.e. the digital signs.

AIM Suite is an AVA component, which passively analyzes the video feed of the audience captured by an embedded camera in real-time, creates and sends viewership information to Analytic Server. After cleansed (removing noises and outliers) on Analytic Server, the viewership information is saved into the data repository in the Cloud. Analytic Server also works as a middleware to provide AVA data access and analytical reports to outside or other components. Data Mining Server provides data mining algorithms and mechanism for learning and querying advertising models. DMM realizes the capabilities of data

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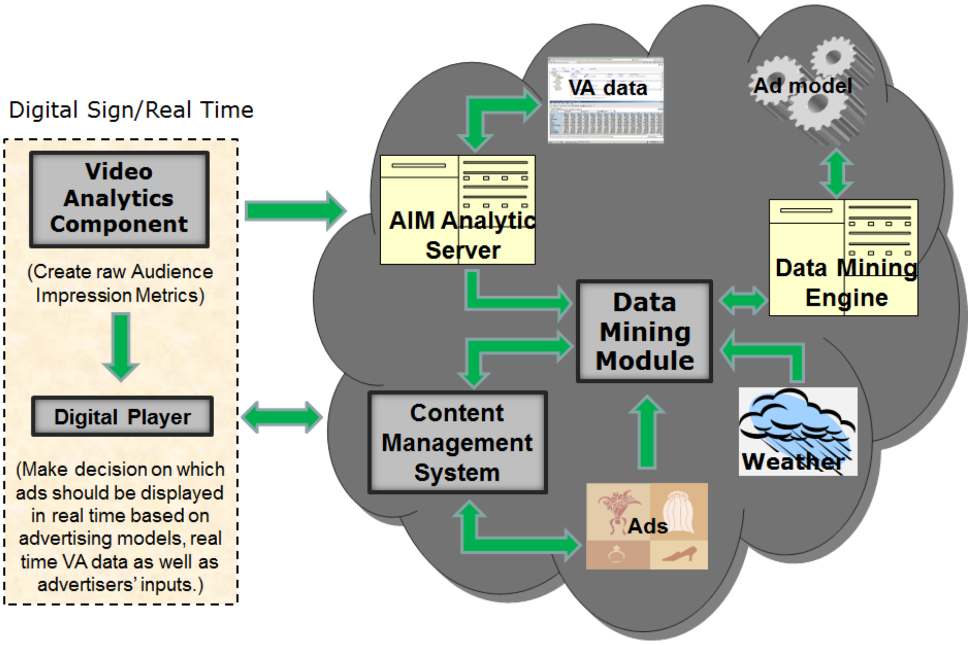

Fig. 1. The IAF Architecture

connection, predictive modeling, model query as well as rule extraction, and automate the processes so as to make these capabilities accessible from other components or applications through web services. CMS consumes advertising models learned by DMM, and take other advertising information as inputs to create customized advertising lists. It also realizes the configuration and management of digital signs, actual ads, advertisers etc. Digital Player takes use of real-time viewership information, advertising models, customized list from CMS and advertisers' inputs etc and makes the final decision in real-time on what ads should be displayed on the digital signs. It also performs the display of the actual ads, creates ad playlist, and sends the playlist to data repository in the cloud.

III. Anonymous Video Analytics

Anonymous Video Analytics (AVA) is a passive and automated audience measurement technology based on computer vision theory [7,8]. It helps digital signage operators to measure marketing ROI by capturing audience data such as total number of viewers, average attention span, and even the gender and age of viewers as they pass by a screen. More advanced data correlations are also possible, such as matching anonymous viewership data with point-of-sale data. AVA plus data correlation provides advertisers a more effective and accurate way to measure the effectiveness of their ads than traditional sampling and extrapolation method.

AVA includes three main steps, human face detection, demographics recognition, and viewing event creation.

A. *Human face detection*

With a standard, low-cost optical sensor embedded in the digital display panel, a video feed of the audience in front of the screen is processed in real-time by the AVA component. The AVA system passively analyzes the video feed and matches sub-sections of each video frame to the general pattern of a frontal human face in real-time. The assumption is that any individual that is looking towards the digital screen will also be front-facing from the perspective of the camera. The face pattern can be learned in an offline process by feeding a large number of anonymous face images to a machine learning algorithm. The algorithm is able to learn the relationship between the type of pixel arrangements (or pixel intensity variations) and human faces.

B. *Demographics recognition*

Furthermore, by feeding face images labeled with demographics, such as gender and age to the above machine learning algorithm, then it can be extended to recognize pixel combinations that correspond to gender, age and other key demographics. At this moment, a mathematical pattern is learned to categorize the facial images into general demographic groups.

C. *Viewing event creation*

Based on the above two steps, AVA component can detect a viewer and record the start time, end time and duration of his viewing behavior. Plus the recognized demographic features, a viewing event is created which states when, where, and which type of viewer watched the digital sign for how long time.

By correlating the viewing events with ad playing events which state when, where, and which ad was displayed for how long time, the AVA system can create various viewing relationship reports and statistics, such as total number of viewers, average attention span etc. These reports and statistics tell how effective the displayed ads are and what kind of audience is being attracted. In this way, it provides digital signage operators with quantitative viewership information and enables them to analyze the ROI.

It should be emphasized that the AVA component is privacy friendly. It only detects the presence of a mathematical human face as well as its demographic features, but it does not identify who the face belongs to. Moreover,

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only viewing events are recorded, which are completely anonymous. And no images or video footage are stored, so there is no way to link back to any specific individual from the viewing events. The audience's privacy is well protected.

IV. Data mining for Targeted advertising

Data mining technology involves exploring large amounts of data to find hidden patterns and relationship between different variables in the dataset [9]. Here we use data mining algorithms to discover the patterns on viewing behaviors of the audience. The basic idea is to show the audience certain ads that have in the past been viewed for a reasonable amount of time by the audience belonging to the same demographics.

A. *Multiple Advertising model training*

For the purpose of capturing the patterns contained in new coming data, two different ways are used to retrain the advertising models, regular retraining and on demand retraining. Regular retraining is triggered regularly, such as weekly or monthly. On-demand retraining is triggered when the performance of the models is lower than a predefined threshold or a retaining request is received from users or operators. Besides, to fully take use of the advantages of different data mining algorithms, multiple data mining algorithms, including Decision Tree, Association Rule and Naïve Bayes, Logistic Regression are used to train advertising models in parallel. The best advertising model or multiple advertising models will be used for ad selection.

B. *Audience targeting methods*

1) *Seeing based targeting*

Seeing based targeting means targeting the audience once the digital sign "sees" the audience. For example, 3 young females and 1 senior male are seen passing by the digital sign, then the advertising models are queried with this input and the most appropriate ad is selected to play. This is the most accurate targeting method give the demographic information of the audience has been captured and used.

2) *Prediction based targeting*

Prediction based targeting first predicts the passers coming in the future period of time and then targets them. For example, it is predicted that 3 young females and 1 senior male will pass by the digital sign within next 20 seconds, then the most appropriate ad is to be selected per the advertising models and prepared to play. This is quite useful in the below scenario. In some cases, if the time cost of the whole targeting process is longer than the audience's dwelling time, that means when the digital player gets the selected ad prepared and displayed on the screen, the audience has looked away and never look back, the seeing based targeting doesn't work.

3) *Context based targeting*

Context based targeting targets the ads just depending on the context, such as targeting date/time, device location, weather info etc. For example, in clear Wednesday morning between 9 AM and 11AM during November and December, an ad for senior males will be selected to play on digital sign A per the advertising models. This is useful when passer type prediction is not reliable or no passer patterns can be discovered from the training data.

C. *Weighted audience counting*

To realize prediction based targeting, passer prediction model is needed to predict the passer type in next time slot. To train this model, weighted audience counting is used to create the training dataset. The count of each passer type is weighted according to the time points when that type of passers passing by the digital sign. For each passer type, we use the following process to calculate its weighted count.

a) Slice time slot T into 10 equal intervals, numbered as t0, t1, …, t9.
b) Label all that type of passer coming within time slot T with a position P = 0, 1, …, 9 according to in which interval they come.
c) The weighted count of this passer type is calculated by $C = \sum_{P=0}^{9} n * (1 - \frac{P}{10})$, where n is the number of the passer labeled as position P.

Table 1 shows an example about passing Female Adult (FA) within time slot T. Then the weighted count for Female Adult in T is $C = 2 * \left(1 - \frac{1}{10}\right) + 1 * \left(1 - \frac{5}{10}\right) + 3 * \left(1 - \frac{8}{10}\right) = 2.9$.

Do the above process for all the passer types in time slot T, a table looking like Table 2 can be got. Repeat the above regarding all the time slots, then a training dataset is created, which includes many rows of weighted counts.

TABLE 1 An example of passing audience

t0	t1	t2	t3	t4	t5	t6	t7	t8	t9
	2FA				1FA			3FA	

D. *Passer prediction models*

Two types of passer prediction models are created as follows.

1) *Passer distribution prediction model*

Based upon the above dataset, specify the 8 passer types as predict variables, and train prediction model. The trained model tells the predicted passer distribution in next time slot.

2) *Dominant passer prediction model*

Based upon the above dataset, select the type of the passer with maximum count as the dominant passer type, and specify the dominant passer type as predict variable, and train prediction model. The trained model tells the predicted dominant passer type in next time slot. For example, the dominant passer type in the above table is Male Adult, whose weighted count is the maximum (3.2).

TABLE 2 An Example of Weighted audience counting

Female				Male			
Child	Young	Adult	Senior	Child	Young	Adult	Senior
0.7		2.9			2.5	3.2	

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E. Advertising Rule Example

1) Seeing based targeting rules

If deviceID = 561 and timeslot = morning and day = Friday and gender = female and age = young and weather = clear and IsWeekend=0 and MediaId=10 and MediaCategory=outdoor, then target potential = 0.9 (at 80% confidence)

2) Prediction based targeting rules

Passer distribution prediction rule:

If deviceID = 561 and time slot = morning and time = 11:00~12:00 and day = Friday and IsWeekend =0 and weather = clear then

NFC = a1*CFC + b1*CFY + c1*CFA + d1*CFS +e1* CMC + f1*CMY + g1*CMA + h1*CMS + i1

NFY = a2*CFC + b2*CFY + c2*CFA + d2*CFS +e2* CMC + f2*CMY + g2*CMA + h2*CMS + i2

NFA = a3*CFC + b3*CFY + c3*CFA + d3*CFS +e3* CMC + f3*CMY + g3*CMA + h3*CMS + i3

NFS = a4*CFC + b4*CFY + c4*CFA + d4*CFS +e4* CMC + f4*CMY + g4*CMA + h4*CMS + i4

NMC = a5*CFC + b5*CFY + c5*CFA + d5*CFS +e5* CMC + f5*CMY + g5*CMA + h5*CMS + i5

NMY = a6*CFC + b6*CFY + c6*CFA + d6*CFS +e6* CMC + f6*CMY + g6*CMA + h6*CMS + i6

NMA = a7*CFC + b7*CFY + c7*CFA + d7*CFS +e7* CMC + f7*CMY + g7*CMA + h7*CMS + i7

NMS = a8*CFC + b8*CFY + c8*CFA + d8*CFS +e8* CMC + f8*CMY + g8*CMA + h8*CMS + i8

Where NFC, NFY, NFA, NFS, NMC, NMY, NMA and NMS respectively mean Next Female Child, Next Female Young, Next Female Adult, Next Female Senior, Next Male Child, Next Male Young, Next Male Adult and Next Male Senior representing the weighted counts of each audience type in the Next time slot; CFC, CFY, CFA, CFS, CMC, CMY, CMA and CMS respectively mean Current Female Child, Current Female Young, Current Female Adult, Current Female Senior, Current Male Child, Current Male Young, Current Male Adult and Current Male Senior representing the weighted counts of each audience type in the Current time slot. And a1, …, a8, b1, …, b8, …, i1, …, i8 are the regression coefficients trained by regression algorithms.

Dominant passer prediction rule:

If deviceID = 561 and time slot = morning and time = 11:00~12:00 and day = Friday and IsWeekend =0 and weather = clear and current dominant passer = senior female then next dominant passer = senior male.

3) Context based targeting rules:

If deviceID = 561 and timeslot = morning and time = 9:00~9:30 and day = Friday and weather = clear and IsWeekend=0 and MediaId=10 and MediaCategory= Media Category 1, then target potential = 0.5 (at 70% confidence)

F. Ad selection based on Advertising models

1) Ad selection for seeing based targeting

Use the available inputs to query the seeing based targeting rules, and summarize the Weighted Target Potential WTP=f(# of Passer, Target Potential, Confidence) for the same ads, then get a list of ads with Weighted Target Potential.

Assume that 3 young females and 1 senior male are seen passing by the digital sign, and the ads within applicable rules are as shown in Table 3. Based Table 3, the weighted target potential can be computed as (# of Passer * Target Potential * Confidence), then summarized in Table 4.

Rank the ad list based on weighted Target Potential, and select top *m* ads as the recommended ads. Correlating with other factors, such as advertiser’s input to finalize the final ads to play.

TABLE 3 AN EXAMPLE OF TARGETING RULES

Passer type	# of Passer	Media Category	Medial ID	Target Potential	Confidence
FY	3	Outdoor	112	0.9	0.8
FY	3	Shoes	116	0.7	0.9
MS	1	Shoes	116	0.5	0.7

TABLE 4 TABLE OF WEIGHTED TARGET POTENTIAL

Media Category	Medial ID	Weighted Target Potential
Outdoor	112	2.16
Shoes	116	2.24

2) Ad selection for prediction based targeting

Regarding passer distribution prediction, we have to calculate the weighted counts of all the passer types in the current time slot, CFC, CFY, CFA, CFS, CMC, CMY, CMA, CMS, and feed them and other available inputs to the passer distribution prediction model, then the weighted counts in the next time slot, NFC, NFY, NFA, NFS, NMC, NMY, NMA, NMS can be figured out. Assuming the weighted counts look like those in the Table 5.

Use the same process as in VI.E.1, the final playing ads can be determined.

Regarding dominant passer prediction, after calculating the weighted counts of all the passer types in the current time slot, CFC, CFY, CFA, CFS, CMC, CMY, CMA, CMS, we just need to select and feed the Current Dominant Passer type and other available inputs to the dominant passer prediction model, and get Next Dominant Passer type. Since only one (the dominant) passer type is considered, # of passer is not used for the calculation.

TABLE 5 VALUES OF ALL THE PASSER TYPE

NFC	NFY	NYA	NFS	NMC	NMY	NMA	NMS
		2.9			2.2		1.6

Use context information (time, location, weather) as input to query context based targeting rule and get a list of ads with Target Potential and Confidence. Rank the list and determine the final playing ads taking into account advertiser’s inputs as in VI.E.1.

V. TARGETED ADVERTISING PROCESS

The process of targeted advertising can be broken down into three phases: learning advertising models, creating playlists, and playing playlists.

A. Learn advertising models

Based on the correlation of the viewership information with ad playing information such as ad name, ad category, DMM is responsible for learning meaningful viewing

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patterns (or advertising models), like when, where, under what weather and to what extent what group of audience is interested in what type of ads. Figure 2 shows the Data flow diagram of DMM. It consists of following subcomponents.

1) Data Connector: Connects and gets access to the training data repository. The data is made of original AVA data, playlist data, weather data and ad data.
2) Data Preprocessor: Realizes necessary data preprocessing actions, like deriving new attributes from original attributes for modeling purpose.
3) Model Constructor: Defines data mining models with specified algorithm, training data scope and training parameters
4) Model Learner: Learn advertising models according to the model definition, also test the learned models against the testing data in terms of accuracy.

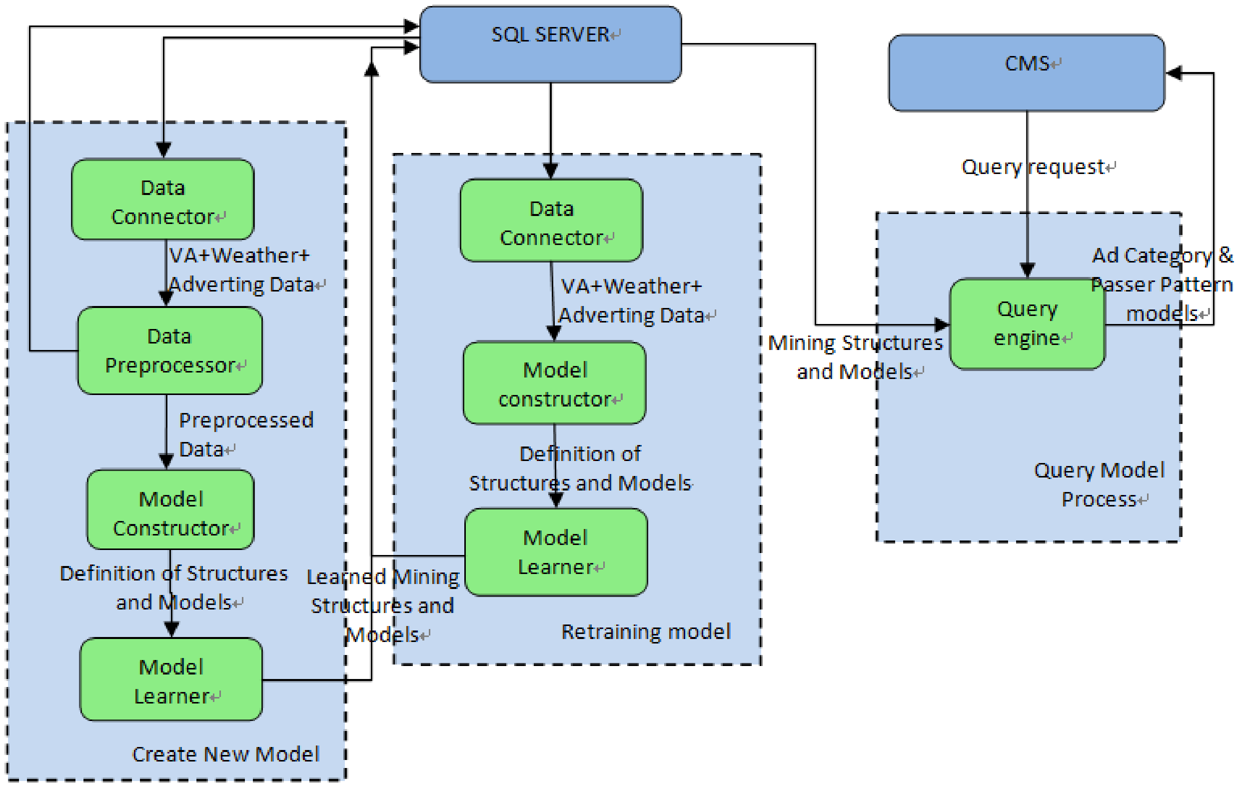

Fig. 2. The data flow diagram of DMM

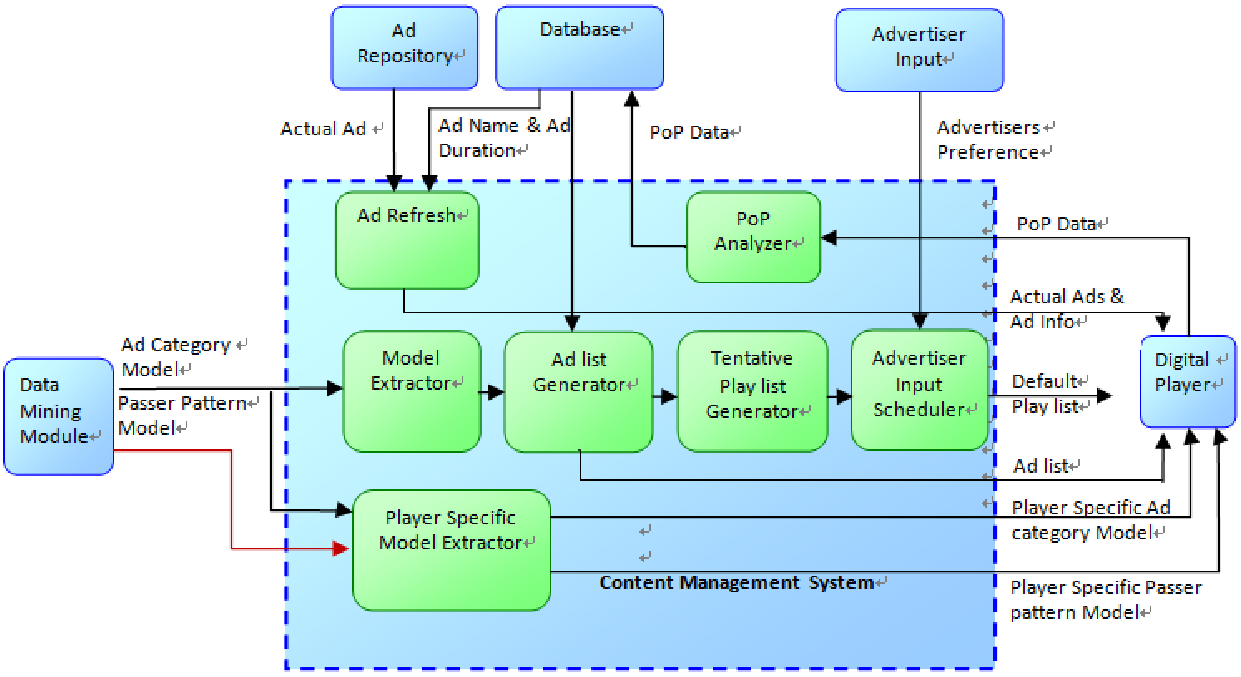

Fig. 3. The data flow diagram of CMS

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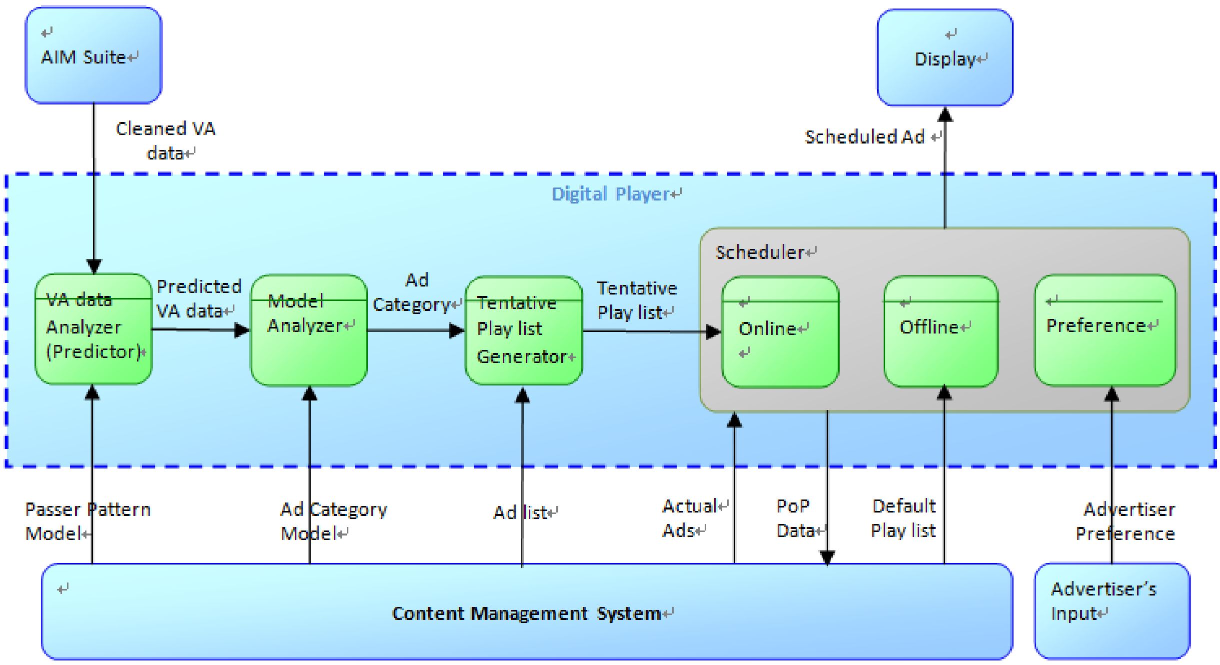

Fig. 4. The data flow diagram of Digital player

5) Query Engine: Both prediction result and model content (such as rules) can be queried against an advertising model. This enables extraction and deployment elsewhere of the model content to achieve better efficiency for real time applications.

B. *Create Default playlists*

After the advertising models are generated, they get transferred to the CMS. CMS then extracts the Ad Categories from the models and creates Ad Category list. The ad information (such as actual ad location) corresponding to the Ad Categories are then fetched from the ad information table. Based on Ad category list, CMS creates initial ad lists, which are modified in Advertiser Input Scheduler. based on the advertisers' inputs. Each Advertiser is assigned certain priority, which rearranges the initial ad lists in Advertiser Input Scheduler. Figure 3 show the data flow diagram of CMS.

C. *Finalize and Play the Playlists*

Finally the shuffered ad lists get transferred to the Digital player. It generates the default playlist by extracting the path from the ad list and then getting the ads from the Ad Repository. The digital player operates in either online or offline mode. In online mode, Digital Player selects an ad based on the probability distribution calculated using advertising models. In the offline mode, Digital Player selects an ad from default playlist based on the scheduling time. It switches between these two modes depending on the confidence level of the advertising models. That means when the confidence beyond some predefined threshold, digital player works in online mode; otherwise, it works in offline mode. Figure 4 shows the data flow diagram of Digital player.

VI. Conclusion

This paper proposed an Intelligent Advertising Framework, which integrates AVA and data mining to realize targeted advertising. By analyzing AVA viewership data collected from previous audience in front of a display, some viewing patterns can be discovered with data mining technology. These viewing patterns or advertising models can be deployed to the digital signs and then used to choose specific ads from the inventory of available content to intelligently target future audiences.

An IAF demo was developed and shown at several Intel internal events and industrial events. The demo got wide recognition and great traction from the industry. An internal pilot of IAF is going on within Intel.

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