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D5.1.2d

Media Planning Engine

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Abstract:

This deliverable outlines the set up of the Next-M media planning engine, which is a part of the Targeted Ad, Editorial and Promotional Content Device. Please do also refer to D2.5.3 for further information.

Keyword list:
media planning, media planning engine, ad exchange, content exchange, reporting, optimisation, Next-M, Next-architectural design, ad planning, optimisation, cost per engagement, media channels, SEM, SEO, reach, targeting, search advertising, 360° campaigns, delivery, monitoring, reporting

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1 Executive Summary

The Targeted Ad and Editorial and Promotional Content Device needs to be divided into: a) the AdServer that is tightly integrated with the NextShare Kernel and that serves as the basis of the free view ad supported monetisation tools of the FairShare MediaService (Next AD) and b) the proprietary stand alone service that is designed to form the basis of the commercial activities of the people and organisations that developed the respective foreground during the P2P-Next project (A-2).

The Targeted Ad and Editorial and Promotional Content Device (TAEPCD) which is developed within WP2 and WP5 consists of two modules - Next-A and Next-M, the media planning engine, which is a development task within WP5.

Next-M encompasses an optimisation module which supports planning of different content types and formats and classic forms of advertising and newly emerging forms such as interactive video ads. It enables users to apply a multitude of campaign optimisation goals and targeting functions (from qualitative awareness building type to quantitative sales channel oriented type with time varying and output device varying features and the ability to reassemble scenes on the spot).

For Next AD advanced optimisation features are of lesser importance, while for A-2 they are at the heart of the buy-side approach (the second stage in entering the market with a commercial product in 2013). Focus is this deliverable is placed on A-2.

2 Next- M Set up

A-2 is composed of 3 modules:

A) an analytics module

B) a targeted AdServer (Next-A) which is suited to manage ad inventory, and to carry and deliver them (sell-side adserver).

C) a media planning engine (Next-M) suited to plan, manage and optimize 360° media and advertising campaigns and to create new types of rich media adverts (buy-side AdServer).

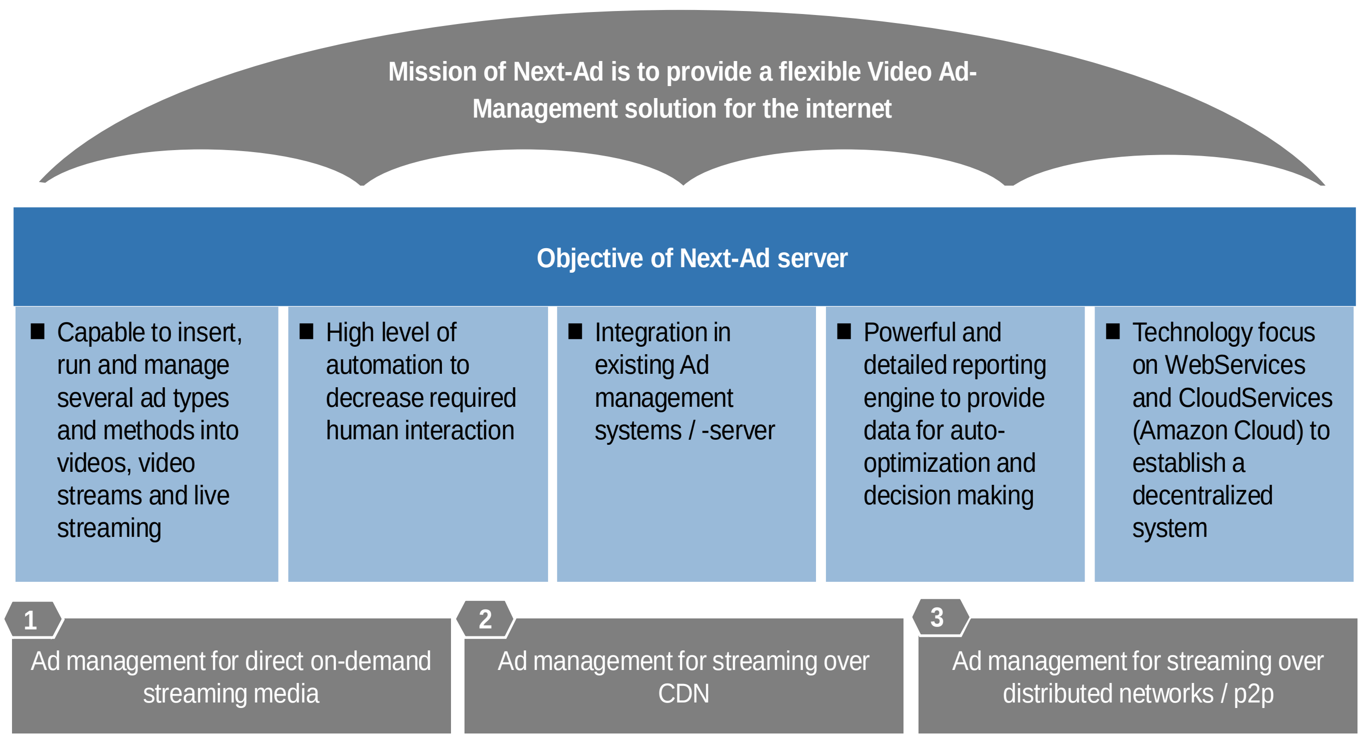

Figure 1: General Scope and Objectives of NextAdServer

2.1 General Scope

Next-M is designed to manage and optimise the complete online and part of the offline ad management value creation chain. It is composed of 2 modules:

a) an analytics and planning module (Next-M APS) and

b) an optimisation, delivery, monitoring and reporting module (Next-M MDR).

Next-M APS is suited to develop cross-media sales and media plans for editorial and promotional content, focusing on adverts.

This applies to the surface web including P2P content offerings. Next-M can be used for display ads (video, audio, text, rich media and stills) affiliate marketing campaigns and SEM/SEO (search engine marketing/optimisation). It can also be used for editorial content if the content is delivered by the producer of the content to the website via e.g. ftp-push or other suitable means without involving middlemen such as content aggregators or broadcasters. Next-M MDR is suited to deliver editorial and promotional contents to websites applying non-intrusive targeting. It is composed of:

a) a multi-objective optimisation module that can be dynamically adjusted across different phases of media campaigns,

b) a monitoring and reporting module, and

c) a module for ad format creation

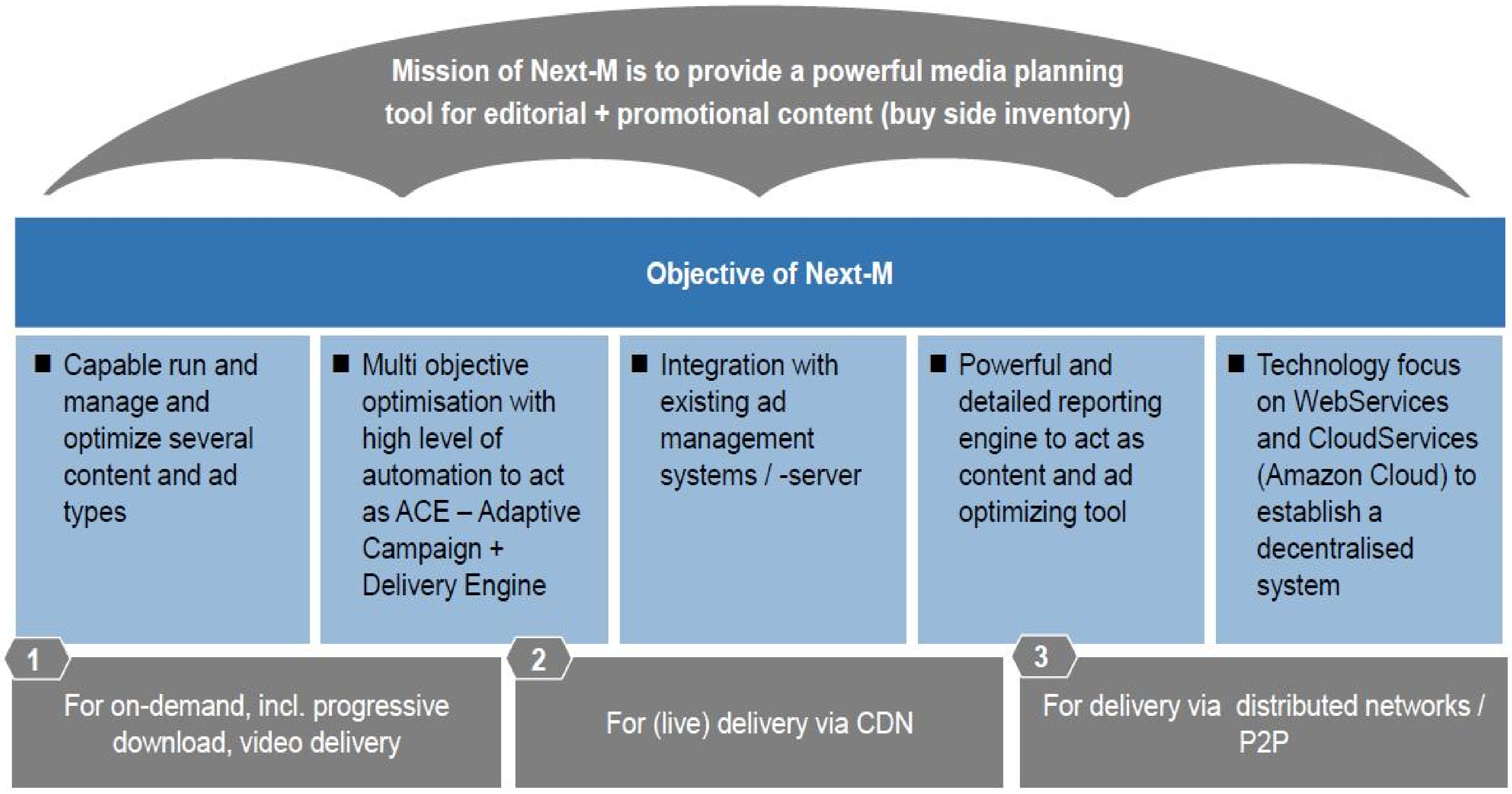

Figure 2: Structure of the Next-M module

The optimisation module constantly processes monitoring and reporting data to optimise the output of the advertising campaign. According to the settings, the optimisation module “shifts” between overall campaign goals and fine controls the performance of a campaign. This incorporates the optimisation of the selected websites, search words, video contents according to the campaign goals (click throughs, conversions, etc.) as well as the performance of the deployed ad forms: e.g. does a certain visual receive more clicks than another visual, the optimisation module will shift deployment to the more successful visual. The same accounts for ad forms, ad surroundings, etc. The optimisation module accounts for the best mix of volume, conversion, and price of a campaign.

The optimisation module can determine the optimal number of ad slots, ad format type, ad frequency and the ad content duration relationship per channel, site or content. Taking into account these parameters will result in calculating a more precise GRP.

Ad Formats

We are currently studying the effect of different ad formats on performance. For a particular content channel or video program, the optimisation module can determine the best ad format or combination of ad formats based on eCPM maximisation, click through rate or conversions. The placement can also be optimised by the ad format. For example, 10 overlay ads in 10 slots may be more effective than 4 video ad rolls: 1 pre roll, 2 mid rolls, and 1 post roll for an episode of the *Daily Show*. Thus, the number of target impressions would change based on the optimisation outcome and ultimately impacts the GRP number.

Ad Frequency

The optimisation module can determine the optimal frequency level. An ad’s effectiveness typically declines with a frequency above 4. However, it can select the right frequency depending on factors like the content type and the state of the user in the purchasing cycle. For example, a frequency of 5 may be ineffective for the wrong user segment but very effective in moving the right segment along the purchasing funnel. In this case, not only does the high frequency result in a higher GRP, but the same GRP on television would not be equivalent in effectiveness.

Ad Content Duration Relationship

The optimisation module can also determine whether a 5 second, 15 second or 30 second ad is best for different placements depending on the length and type of content. The ad duration algorithm can also maximise the number of ad slots for a particular content, site or channel. For example, two 5 second mid-rolls in sequence instead of one 15 second mid roll may be preferable for the news channel versus the sports channel. The ad content duration is another parameter that the module can consider when determining the maximum number of target impressions. Ad format, ad frequency and ad content duration relationship are some of the elements that can be optimised in order to maximise both the reach and frequency variables of the GRP equation.

Next-M provides state of the art online measurements as provided by the industry standard players, coherent to the comprehensive IAB guidelines on online metrics like the 2004 published “Interactive Audience Measurement and Advertising Campaign Reporting and Audit Guidelines”[1]. Additionally the IAB has published “Broadband Video Commercial Measurement Guidelines”[2] in 2006, updated in 2009 under the title “Digital Video Ad Impression Measurement Guidelines”[3].

To got beyond state of the art it is also necessary to report metrics giving information related to innovative video adverts. While a displayed classic web ad is a “view”, for video ads it is important to know how long the video ad was watched, how much of the video was viewed at normal speed, was audio mute activated or not, etc.

Performance Indicators	Description
AdImpression	Ad insertion
AdClick	Click on the advertisement.
Click Through Rate (CTR) - Conversion	CTR (proportion between AdClick and AdImpression).
Engagement (Interaction) Rate	All engagements (interactions) in proportion with the AdImpressions.
Average Engagement (Interaction) Time	How long has the user been interacting with the advertising material? (played, paused, rewind)
Video View in %	Percentage of viewed video material?
Views	How often has the video been viewed?
Video Played 25%	How often have 25% of the video been viewed?
Video Played 25% Rate	% in total views.
Video Played 50%	How often have 50% of the video been viewed?
Video Played 50% Rate	% in total views.
Video Played 75%	How often have 75% of the video been viewed?
Video Played 75% Rate	% in total views.

Figure 3: Key Performance Indicators for P2P-Next AdServer 1/2

1 http://www.iab.net/media/file/Global_meas_guidelines.pdf
2 http://www.iab.net/media/file/standards_pdf_BB_measurementGuidelines_051006.pdf
3 http://www.iab.net/media/file/dig_vid_imp_meas_guidelines_final.pdf

Performance Indicators	Description
Video Played 100% - Completed Play	How often have 100% of the video been viewed?
Video Played 100% - Completed Play Rate	% in total views.
Average Time Video Played (Time Spend Viewing)	Average viewing time.
Video Start Rate	How often has the video been started?
Pause	How often has the video been paused?
Resume	How often has the video been resumed?
Fullscreen	How often has the full screen mode been switched on?
Fullscreen Exit	How often has the full screen mode been switched off?
Rewind	How often has the video been wind back?
Fast-Forward	How often has the video been fast-forwarded?
Replay	How often has the video been replayed?
Audio Mute	How often has the video been muted?
Unmute	How often has the sound been switched back on?

Figure 4: Key Performance Indicators for P2P-Next AdServer 2/2

The IAB is trying to set a standard on these issues in the recently published paper “Digital Video In-Stream Ad Metrics Definitions”[4]. The work in P2P-Next will follow these guidelines.

2.2 Multi Criteria Optimisation and Decision Making

Multiple criteria optimisation seeks to simultaneously optimize two or more objective functions under a set of constraints. It has a great variety of applications, ranging from financial management, energy planning, sustainable development, to aircraft design.

In recent years, the multiple criteria optimisation research community has actively involved in the field of data mining (See, for example: Yu 1985; Bhattacharyya 2000; Francisci & Collard, 2003; Kou, Liu, Peng, Shi, Wise, & Xu, 2003; Freitas 2004; Shi, Peng, Kou, & Chen, 2005; Kou, Peng, Shi, Wise, & Xu, 2005; Kou, Peng, Shi, & Chen, 2006; Shi, Peng, Kou, & Chen, 2007).

The multicriteria analysis (MA) and multicriteria optimisation (MO) problems are multicriteria decision making problems. In MA and MO problems several criteria are simultaneously optimized. In the general case there does not exist one alternative(solution), which optimizes all the criteria.

The solution of MA or MO problem is a set of alternatives, called a set of the non-dominating or of the Pareto optimal alternatives. Each alternative in this set could be a solution of the multicriteria problem. In order to select one alternative, it is necessary to have additional information set by the so-called decision maker (DM). The information that the DM provides reflects his/ her global preferences with respect to the quality of the alternative sought.

The methods developed to solve MA problems, can be grouped into three separate classes: weighting methods, outranking methods and interactive methods. The main element in the

4 http://www.iab.net/media/file/standards_pdf_BB_measurementGuidelines_051006.pdf

weighting methods is the way of determining the criteria weights, which reflect DM's preferences to the highest degree. Many methods for criteria weighting have been developed. A value tradeoff method has been proposed as well as an analytic hierarchy process (AHP weighting method), using pair-wise criteria comparison. This latter method is generalised to reflect DM's uncertainty about the estimates in the reciprocal matrix. A direct ranking and rating method has also been proposed.. A mathematical programming model with sensitivity analysis has been used in to determine the intervals of weights, within which the same ranking result is produced. The weighting methods use a DM's preference model, which does not allow the existence of incomparable alternatives and the preference information obtained by the DM (different types of criteria comparison) is sufficient to determine whether one of the alternatives must be preferred or whether the two alternatives are equal for the DM.

The outranking methods use a DM's preference model which allows the existence of incomparable alternatives and the preference information obtained by the DM may be insufficient to determine whether one of the alternatives is to be preferred or whether the two alternatives are equal for the DM. The criteria and the alternatives are not compared by the DM in these methods, but he/she has to provide the so called inter- and intra-criteria information.

Some of the more well-known representatives of the outranking methods are ELECTRE I-IV methods, PROMETHEE I-II methods, TACTIC method and others.
In order to solve MA problems with a large number of alternatives and a small number of criteria, "optimisationally motivated" interactive methods have been suggested (VIMDA method, aspiration-level method, LBS method, RNIM method. The first two methods use the first type of DM's preference model and the DM must define the desired or acceptable values of the criteria at every iteration. The last two methods use the second DM's preference model and the DM has to give not only the desired values of the criteria but also inter- and intra-criteria information at every iteration.

There are two main approaches in solving MO problems: a scalarising approach and an approximation approach. One of the most developed and widespread methods for solving multicriteria optimisation problems are interactive methods. MO problems are treated in these algorithms as a decision making problem and the emphasis is put on the real participation of the DM in the process of its solution.

The interactive methods are the most developed and widespread due to their basic advantages – a small part of the Pareto optimal solutions must be generated and evaluated by the DM; in the process of solving the MO problem, the DM is able to learn with respect to the problem; the DM can change his/her preferences in the process of problem solution; the DM feels more confident in his/her preferences concerning the final solution.

The interactive methods of the reference point (direction) and the classification-oriented interactive methods) are the most widely spread interactive algorithms solving MO problems. Though the interactive methods of the reference point are still dominating, the classification-oriented interactive methods enable the better solution of some chief problems in the dialogue with the DM, relating to his/her preferences defining, and also concerning the time of waiting for new non-dominated solutions that are evaluated and selected.

A variety of methods to approximate the set of Pareto optimal solutions of different types have been proposed. Some methods are exactly equipped with theoretical proofs for correctness and optimality while some other methods are heuristic and often theoretically unsupported. The main representatives of the heuristic methods are the multicriteria genetic (evolutionary) methods.
The MO problem is treated in these methods rather as a vector optimisation problem, than as

a decision making problem and the stress is placed on the determination of a subset of potential Pareto optimal solutions, which approximates well enough the whole Pareto optimal set.

This is achieved, supporting a population of candidates for the approximating subset during the whole process of optimisation. This population is improved at each iteration with the help of different operators, modeling the basic processes of biologic genetic such as selection, recombination and mutation.

The software systems supporting the solution of MA problems can be divided in two classes – software systems with general purpose and problem-oriented software systems. The general-purpose software systems aid the solution of different MA problems by different decision makers. One method or several methods from one and the same group are usually realized in them for solving MA problems. The problem-oriented MA systems are included in other information-control systems and serve to support the solution of one or several types of specific MA problems. Hence some simplified user's interface modules are usually realized in them. That is why methods from different groups of MA methods are included in some of these systems.

The general-purpose software systems developed, Web-HIPRE, HIVIEW, ELECTRE III-IV, PROMCALC and GAIA, Decision Lab, VIMDA realize one method or several methods from one and the same group, above described. Two representatives of the problem-oriented systems are: the FINCLAS system for financial classification problems and the Agland Decision Tool for agricultural properties.

The software systems developed to aid the MO problems solution can be divided also into two groups: software systems of general purpose and problem-oriented software systems. Some well-known general-purpose software systems, which solve problems of MO, are the systems VIG, NIMBUS, DIDAS, CAMOS, LBS, DINAS, MOLP-16, MONP-16, MOIP.

The first type comprises the interactive algorithms of the reference point and of the reference direction. These are systems such as DIDAS, VIG, CAMOS, DINAS and LBS. The second type of interactive algorithms includes the classification-oriented algorithms. These interactive algorithms are built in the systems NIMBUS, MOLP-16, MONP-16 and MOIP. One representative of the problem-oriented systems is the ADELAIS system for portfolio selection.

There is no commercial software package for advertising and media available, although there are a number of decision support systems and tools for data mining and financial optimisation problems.

Many data mining tasks, such as classification, prediction, clustering, and model selection, can be formulated as multi-criteria optimisation problems. Depending upon the nature of problems and the characteristics of datasets, different multi-criteria models can be built.

Utilizing methodologies and approaches from mathematical programming, multiple criteria optimisation is able to provide effective solutions to large-scale data mining problems. An additional advantage of multi-criteria programming is that it assumes no deterministic relationships between variables (Hand & Henley, 1997).

Recently, the multi-criteria or multi-objective optimisation-based methods have been proposed as another option for data mining tasks. For instance, Bhattacharyya proposed a multi-objective model for direct marketing (2000); Francisci and Collard addressed the interestingness measure of dependency rules by formulating the scenario as a multi-criteria problem (2003); and Kou, Peng, Shi, and Chen built a multi-criteria convex quadratic programming model for credit portfolio management (2006).

If a data mining task can be modeled as optimisation problems with multiple objective functions, it can be cast into the multi-criteria optimisation framework. Many data mining functionalities, such as classification, prediction, and interestingness measure, can be formulated as multi-criteria optimisation problems. For example, in multi-criteria optimisation context, the classification problem can be stated as one of simultaneously minimizing misclassified points and maximizing correctly classified points.

The established methodologies and procedures for solving multi-criteria optimisation problems and incorporating the results into the business decision process by the discipline of multi-criteria decision making (MCDM) can be applied to these data mining tasks.

Currently, the main focuses of multiple criteria optimisation in data mining include: model construction, algorithm design, and results interpretation and application.

Model construction refers to the process of establishing mathematical models for multi-criteria data mining problems, which exist in many data mining tasks. For example, in network intrusion detection, the goal is to build classifiers that can achieve not only high classification accuracy, but also low false alarm rate. Although multiple objectives can be modeled separately, they normally can not provide optimal solutions to the overall problem (Fonseca & Fleming, 1995). Furthermore, a model may perform well on one objective, but poorly on other objectives. In this kind of scenario, multiple criteria optimisation can be used to build models that can optimize two or more objectives simultaneously and find solutions to satisfy users' preferences.

Algorithm design is a set of steps that takes raw data as input and generates solutions as output. Specifically, algorithm design normally includes data preparation, optimisation approach, and model assessment.

1.Data preparation: Raw data are selected and cleaned according to the requirements of data mining tasks. In addition, data need to be formatted into appropriate forms. Since multiple criteria optimisation models can handle only numeric inputs, categorical attributes need to be transformed into numeric types.

2. optimisation approach: There are three main approaches to multiple criteria optimisation (Freitas, 2004): (i) convert multiple objectives into a single-criterion problem using weight vectors; (ii) prioritize objectives and concentrate on objectives with high priorities, which is called the lexicographical approach; (iii) find a set of nondominated solutions and allow business users to pick their desired solutions, which is also known as the Pareto approach. Each approach has its advantages and disadvantages. The first approach, reformatting multi-criteria as a single-objective problem, is by far the most popular one in data mining field due to its simplicity and efficiency.

3. **Model assessment:** Results of models, such as accuracy and generality, are assessed according to predefined criteria.

Depending on application domains and user preferences, results have to be interpreted differently. In media and marketing, multiple criteria optimisation can provide class labels and probability scores as well as decision support or even decision making. The application of multiple criteria optimisation techniques can be expanded to more data mining and amrketing tasks.

So far classification task is the most studied problem in the data mining literature. Multiple criteria optimisation could be applied to many other data mining issues, such as data preprocessing, clustering, model selection, and outlier detection (Mangasarian, 1996). Another direction is to examine the applicability of the lexicographical and Pareto approaches in large scale data mining problems.

2.4 Licensing Options in A-2

A licensee has special methods and options to choose from:

a) Manual Single Factor Optimisation

The user selects one optimisation goal such as CPC. Results (adverts, channels and sites) are displayed on a hourly, daily or weekly basis In a predefined time interval, the user can now start a series of manual optimsation runs and can discharge completely or allocate less budget and ad time to certain adverts, sites or channels while increasing others.

b) Semi-Automated Single Factor optimisation

Based on a set of predefined criteria the system optimizes the allocation of adverts, ad times and budgets on its own and makes suggestions for changing a campaign. The user has the option to accept, modify or discharge the suggestions before they enter the system and be executed.

c) Fully Automated Single Factor Optimisation

The system carries through the campaign completely on its own. until the performance falls below a certain threshold and will be automatically stopped then (or the budget is fully consumed which is the preferred option, of course) .

d) Manual Multi Criteria Optimisation

Method a) is extended and applied to work with multi criteria and factor analysis and optimisation. The user can choose from the methods displayed in g).

e) Semi automated multi criteria automisation

The same as in d) applies to method b.

f) Fully Automated Multi Criteria Optimisation

The same as in e) applies to method c.

g) Definition of the optimisation function (Fitness Function)

The definition of the optimisation function is based on the criteria licensing model and capabilities of the user.

Model 1a – simple basic

Der User defines a few important parameters of his campaign on the basis of a questionnaire and a few parameters of the optimisation method (rule based and explanatory, numeric, black box accepted etc.). The system chooses the fitness function/ optimisation function. Limited simulation runs and a few optimisation runs will be carried through selected from a few available parameters.

Model 1b– simple premium

The method as in 1a is carried through but with an extended set of calculations. After the system has been trained and tested the best 5 methods will be selected. These perform live and are in a constant competition with each other. The best system will be used until another of the 5 selected systems takes over and yields better results.

Model 2a – advanced basic

The user has a few optimisation functions and variables at hand but can develop its own optimsation system based on a set of methods and operations that are available. The method is for math and statistics savvy users only.

Model 2b – advanced premium

There is a combination of model 2a und 1b.

Model 3a – super basic

The user has access to all methods and optimisation functions in the kit to develop its own system. Live simulation capabilities are limited though to basic level.

Model 3b – super premium

This is the full "monty" - a combination of the models 1b und 3a.

3 Next Steps

V3.0 of Next-M has been completed in time. It comes in two sub versions. Version 1 is part of the Next-AD AdServer that supports the FairShare MediaService (see deliverables of WP2), version 2 is part of the stand alone proprietary A-2 service.