Optimizing Google Shopping Campaigns Structures With Query-Level Matching

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Abstract. How to bid on a Google shopping account (set of shopping campaigns) with query-level matching like in Google Adwords.

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1 Introduction

In a Google Adwords campaign, one can define the bid entities (ie the criterions) with a set of keywords and associated matching types (exact, phrase or broad). Those keywords are compared against the user query, which allows for fine tuning of the user intent. As in a Google Shopping campaign, the criterions are defined as the leaves of a product tree defined over the product feed of a merchant. Fundamentally, in this case, the bidding is done on the catalog of the merchant, not on the user intent. In this paper, we aim at taking back control of the user intent with a carefully designed campaign structure. In particular, we consider a set of keyword of interest that we want to be able to match to the user query and associate to a particular set of items in a Google Shopping account for a specific bid.

1.1 Structure Of A Google AdWords Campaign for merchants

We will assume, as in every Google Shopping campaign, that the merchant is able to construct a product feed, which contains the list of all of its products. Each description of a product has multiple features, which contains at least a unique identifier itemID, a brand, and a set of categories. We present below a simple structure of a Google AdWords campaign instance in the special case of a merchant campaign.

1. nike shoes $\Rightarrow$ CPC1 $\Rightarrow$ LandingPage1
2. large tee-shirt $\Rightarrow$ CPC2 $\Rightarrow$ LandingPage2, LandingPage3
3. garmin chronometer $\Rightarrow$ CPC3 $\Rightarrow$ LandingPage4
4. adidas running shoes $\Rightarrow$ CPC4 $\Rightarrow$ LandingPage5

In general, the landing pages would contain items that the merchant want to sell. As a shortcut, we will associate a keyword with a set of items.

\[
\text{keyword} \Rightarrow \text{CPC} \Rightarrow \text{set of itemIDs } I = \{i_1, i_2 \ldots i_k\}
\]

We will call each of those line a rule. It means that ideally a given query keyword should match a product $i_j$ in $I$, bidding at most the value of Cost Per Clic (CPC) on it.

Let $SK$ the set of all keywords and $SR$ the set of all rules. The number of such keywords and rules is denoted $n = |SK| = |SR|$, $n$ can vary from hundreds to thousands of keywords or even millions. However, active keywords at a given time, meaning those really leading to conversions during the last days/months, are in general much less, a few hundreds. Our method is able to handle thousands of keywords but is generally applied to the few hundreds which convert.
negative keywords

Product tree

Filter
case when considering rules leading to conversions. This implies that all keywords would fit as negative

than

is associated a product tree.

and faces the AdGroups. An AdGroup can also be seen the same way, a jar with a filter, but to which

in an exact, phrase or large match. If not the case, the keyword goes through the filter, enters the jar,

negative keyword

w(phrase)

exact

large

s

large shoes

(CPC1 CPC2 CPC3 CPC4)

nike shoes

reebok shoes

nike large shoes

Fig. 1: an AdGroup of 6 items with a product tree. All negative keywords are of large type.

1.2 Structure Of A Shopping Campaign

Each campaign might contain a set of negative keywords. A negative keyword forbids the entry of the corresponding query keyword in a campaign. Those keywords are called campaign negative keywords.

A campaign is structured in AdGroups, each AdGroup corresponding to an item set, placed in a decision tree (named product tree - possibly a single leaf) built using the features as branches. A leaf of such a tree is named criterion. Each AdGroup might also contain a set of negative keywords. Figure 1 represents an instance of an AdGroup with a product tree.

Let \( p \) be a keyword, we denote \( w(p) \) the set of continuous subwords that \( p \) contains. For instance, \( w(\text{nike large shoes}) = \{\text{nike}, \text{large}, \text{shoes}, \text{nike shoes}, \text{large shoes}, \text{nike large shoes}\} \). We denote \( s(p) \) the set of words composing \( p \).

The negative keywords of a campaign or an AdGroup can be of three types: exact, large or phrase, which differ on the type of matching against the query. An exact negative keyword matches a query which is exactly the keyword. A phrase negative keyword \( p \) matches any query \( q \) such that \( p \in s(q) \). A large negative keyword \( p \) matches any query \( q \) such that \( s(p) \in s(q) \).

A shopping campaign can be conceived as a jar which lid is a filter composed of negative keywords. A query keyword tries to enter the jar, but is stopped by the filter if one negative keywords matches, in an exact, phrase or large match. If not the case, the keyword goes through the filter, enters the jar, and faces the AdGroups. An AdGroup can also be seen the same way, a jar with a filter, but to which is associated a product tree.

The limit on the number of keyword of a campaign or an AdGroup is denoted \( L \) and is at this time around 20000. One problem which intrinsically complicates our approach below is that \( L \) might be less than \( n \). In this version of our article, we consider that \( n < L \), which is, as stated above, quite always the case when considering rules leading to conversions. This implies that all keywords would fit as negative in either campaigns or AdGroup negative keywords sets.

The way a query keyword passes through campaigns and AdGroups is named its trajectory. Figure 2 shows some trajectories.

Fig. 2: A shopping campaign containing 3 AdGroups with some keyword trajectories. All negative keywords are of large type.
1.3 Structure Of A Shopping Account

A shopping account may contains many campaigns, that are classified by priority. There are 3 priority levels: high, medium and low. Given a query keyword, a match is attempted in every campaign by decreasing priority order. Once a match found, the remaining campaigns are not any more checked. Figure 3 shows such an account with some query keywords trajectories.

![Diagram of shopping account with high, medium, and low priority campaigns]

Fig. 3: A shopping account containing 3 campaigns of high, medium and low priorities.

1.4 Motivation And Objectives

The main drawback of using google shopping is that the matching between the query keyword and the items is decided by Google with very low control to the user. This is a deep difference with AdWords campaigns. This induces many difficulties for digital advertising agencies to optimize the shopping account and to model the bids.

However, some high-tech agencies recently proposed new shopping account structures using the campaign priorities and/or the keywords to better control the matching. This requires to better control the trajectories of queries through the account, whatever the query.

To our knowledge, two main approaches have been designed up to far:

1. use campaign level priorities to distinguish between general, long tail, and specific requests [5,3].
2. use AdWords rules and campaign negative keywords to design 2 levels campaign account guiding query keyword trajectories to land in a specific AdGroup [1].

In this article we mix and extend both approaches to:

1. use the 3 campaign priorities to distinguish general, less general but branded, and eventually query keywords that has been chosen in a pre-defined AdWord campaign
2. use AdWords rules and campaign negative keywords to design 3 levels campaign account guiding query keyword trajectories to the set of item(s) specified by the rule its belongs to.
3. minimize the number of negative keywords, of campaigns and AdGroups, to reach this goal.

This structure permits to specify a CPC for each rule, thus getting the lowest possible granularity as a pre-require for a smart bidding strategy.

This article is structured as follows: in Section 2 we first explicit the structure of a campaign account we propose and prove that it corresponds to what we expect. We bound in Section 3 the number of keywords required. We then explain in Section 4 how to strongly lower on average the negative keyword number using a keyword reduction based on an ad-hoc heuristic. We explain in Section 5 how to perform several types of update on this structure. Eventually, in Section 6 we present a complete example.

Let us denote $SB$ the set of brand names the merchant sells, and $SNB$ the set of brand names that the merchant does not sell but are known in the retail domain of the merchant. For instance, a merchant can sell the brands $nike$ and $adidas$ but not $reebok$. Then $SB = \{nike, adidas, garmin\}$ and $SNB = \{reebok\}$. For each brand $b \in SB$ we assume a product tree $PT(b)$ to be given. For instance for the brand $nike$, a $PT(nike)$ could be $PT(nike) = [[\text{shoes}, \text{CPC12}] \ [\text{jogging}, \text{CPC14}]$ $[\text{others}, \text{CPC15}]]$, where $\text{shoes}$ and $\text{jogging}$ are two pre-defined categories.
2 Our Structure Of Shopping Account

We propose the following 3 levels structure. The first level is a high priority campaign which filters queries that are the more general, non branded and do not belong to SK. The medium level is again a single campaign, but which does not filter branded keywords that are not in SK. The third level consists of a series of campaigns which permit to exactly match the keywords in SK.

2.1 High-priority Campaign $C_1$

We create one high priority campaign $C_1$ which role is to filter all \textit{a priori interesting} keywords, that is, the keywords which are stopped by $C_1$ are $SK(exact) \cup SB(phrase) \cup SNB(phrase)$. When one keyword passes the filter, it is matched by Google to possibly a set of items on which we have no control. Thus the idea is to fix low value CPCs at this point, but to keep watching those “referees” which could be integrated latter to the structure if they truly convert. Figure 4 shows such an high level campaign.

![Fig. 4: High-priority campaign. Negative keywords are $SK(exact) \cup SB(phrase) \cup SNB(phrase)$, filtering all the pre-defined keywords and also keywords not in $SK$ but containing brand names (of the site or not).](image)

2.2 Medium-priority Campaign $C_2$

![Fig. 5: Medium-priority campaign. Negative keywords are $SK(exact) \cup SNB(phrase)$, filtering all the pre-defined keywords. However, keywords not in $SK$ but containing brand names in $SB$ pass the negative filter at this campaign level. One AdGroup by brand name.](image)

The medium-priority campaign $C_2$ (fig. 5) is devoted to filter branded keywords that are not in $SK$. Then the CPC are adjusted by brand name. The negative of the campaign are $SK$ and $SNB$ (but not $SB$). The campaign contains one AdGroup per brand name, say $b_i \in SB$. The AdGroup corresponding to $b_i$ has $SB \setminus b_i$ for negative keywords. This way, only queries containing $b_i$ pass the filter. The AdGroup may contain a product group allowing to better adjust CPCs with the brand features.
2.3 Low Priority Campaigns $C^i_3$

The set of keywords $SK$ is divided in $k$ groups $sk_1, sk_2, \ldots, sk_k$. We create $k$ campaigns $C^i_3$, $1 \leq i \leq k$, each $C^i_3$ being built to match all keywords in $sk_i$ and only them, and thus has for negative keywords $SK \setminus sk_i \cup SNB$. Then, one AdGroup is created for each keyword $l \in sk_i$, $1 \leq l \leq |sk_i|$, filtering all the other keywords in $sk_i$. Thus the AdGroup corresponding to $j$ has $sk_i \setminus j$ for negative keywords. Figure 6 shows such a series of campaigns on our continuing example, where $k = 2$ and $sk_1 = \{nike shoes, large tee-shirt\}$, $sk_2 = \{garmin chronometer, adidas shoes\}$.

![Diagram showing low priority campaigns]

Fig. 6: One low-priority campaign (among $lp$ such campaigns) corresponding to the set $sk$ of keywords. Campaign negative keywords are $(SK \setminus sk) \cup SNB$. The campaign contains $sk$ AdGroups, one for each keyword in $sk$. The AdGroup corresponding to $k_i \in sk$ has $sk \setminus k_i$ as negative keywords.

2.4 Structure Main Property

We prove the three main properties of our structure. Let $q$ be a query keyword.

Property 1. If $q \in SK$, there exist a unique $C^i_3$ such that $q$ is associated with a unique AdGroup of $C^i_3$.

Proof. $q$ does not enter $C_1$ nor $C_2$ since it belongs to $Neg(C_1)$ nor $Neg(C_2)$. $q$ is then stopped by all but one low priority campaign, say $C^i_3$, since it belongs to a unique set $sk_k \in SK$ and that all others low priority campaigns stop $sk_k$. In $C^i_3$, $q$ passes the filter of a unique AdGroup corresponding to the keyword $q$ itself.

The following property states the case when a query does not match any keyword in $SK$ but contains a brand name.

Property 2. If $q \notin SK$ but there exits a unique $w \in w(q)$ such that $w \in SB$, $q$ is associated to a unique AdGroup in $C_2$.

Proof. As $SB \in Neg(C_1)$ as phrase, $q$ does not enter $C_1$. Then $q$ is tested against $C_2$. As $q \notin SK$, and that $SB \notin Neg(C_2)$, $q$ enters $C_2$. Then $q$ is blocked by all AdGroups containing $w$ as phrase. Only one AdGroup (by construction) does not stop $w$, and $q$ is thus associated to this AdGroup.

The following property states the case when a query does not match any keyword and does not contain a brand name.

Property 3. If $q \notin SK$ and $w(q) \cap SB = \emptyset$, $q$ is recognized in $C_1$.

Proof. $q$ is not stopped by any negative keyword of $C_1$, thus $q$ passes through the filter of $C_1$. 

5
3 Bound On The Number Of Negative Keywords

Our structure permits fine-grained bidding on queries by assigning to each rule a specific AdGroup which is only reachable by the keyword of the rule. Let us now count and optimize the number of negative keywords it requires. We recall that \( n = |SK| \). We denote \( m = |SB| \) and \( m' = |SNB| \) and that \( k \) is the number of splits of \( SK \).

3.1 Number Of Negative Keywords

1. 1 high priority campaign, \( n + m + m' \) campaign negative keywords.
2. 1 medium priority campaign, \( n + m' \) campaign negative keywords.
   (a) \( m \) AdGroup with \( m-1 \) negative keywords each

Thus the number of negative keywords for the high and medium priority campaign is \( 2n + 2m' + m + (m-1)m = 2n + 2m' + m^2 \).

Let us count now the negative keywords of low level campaigns. Each \( sk_i \) set leads to a campaign \( C_i \) which contains \( \sum_{i,1 \leq l \leq k} |sk_i| + m' \). The total over all \( C_i \) is then

\[
\sum_{1 \leq i \leq k} \left( \sum_{1 \leq l \leq k} |sk_i| + m' \right) = (k-1) \sum_{1 \leq i \leq k} |sk_i| = (k-1)n + km'
\]

campaign negative keywords.

Each campaign \( C_i \) also contains \( |sk_i| \) AdGroups, each such AdGroup containing \( |sk_i| - 1 \) AdGroup negative keywords, thus \( |sk_i| + (|sk_i| - 1) = |sk_i|^2 - |sk_i| \) keywords. Summing over all \( C_i \), this leads to

\[
\sum_{1 \leq i \leq k} |sk_i|^2 - |sk_i| = \sum_{1 \leq i \leq k} |sk_i|^2 - kn
\]

The whole total number of negative keywords is thus \( NK = 2n + 2m' + m^2 + (k-1)n + \sum_{1 \leq i \leq k} |sk_i|^2 - n = m^2 + (k + 2)m' + kn + \sum_{1 \leq i \leq k} |sk_i|^2 \).

3.2 Worst Case Optimization

We want to minimize \( NK \). Because of the square in the last term. This appears when the \( sk_i \) are all of the same cardinal of \( n/k \) keywords, leading to \( NK = m^2 + (k + 2)m' + kn + k(k+1)^2 \). Considering that \( m \) and \( m' \) are small compared to \( n \), the minimum is reached when \( k \) is close to \( \sqrt{n} \). This leads to a number of keywords of \( NK = m^2 + (\sqrt{n} + 2)m' + 2\sqrt{n}n \). We show below some values on real data to visualize the number of negative keywords this approach requires.

| Site | \( SK \) | \( m \) | \( m' \) | \( NK \) |
|------|---------|-------|-------|-------|
| Site1| 3000    | 100   | 30    | 340337|
| Site2| 7000    | 1     | 0     | 1171324|
| Site3| 10000   | 30    | 20    | 2002940|
| Site4| 10000   | 1000  | 40    | 3002040|

4 Lowering The Number Of Negative Keywords

The total worst case number of negative keywords is high compared to the number of \( NK \). We propose now an heuristic to reduce on average this number of keywords. This technique is based on a new notion of “eraser” that we define formally.

**Definition 1.** A large eraser of a set \( P = \{p_1, \ldots, p_j\} \) of keywords is a set of words \( e \) such that \( e \in s(p_i) \).

**Definition 2.** An exact eraser of a set \( P = \{p\} \) of a single keyword is the keyword \( p \) itself.
The set of erasers (large or exact) of $P$ is denoted $E(P)$. The image of a given eraser $E$ relatively to a set $P$ is the set of keyword(s) of $P$ it erases. Its size is denoted $I_P(E)$. Note that if $E$ is an exact eraser on $P$, $I_P(E) = 1$. When the set of keywords $P$ is non-ambiguous, $I_P(E)$ is simplified as $I(E)$.

Usually the set $P$ is contained in a larger set, say $SP$, and we introduce the notion of strict eraser.

**Definition 3.** Let $SP = \{p_1, \ldots, p_j\}$ and $P \subseteq SP$. A strict eraser of $P$ relatively to $SP$ is an eraser of $P$ which is not an eraser of any $p \in SP \setminus P$. The set of strict erasers of $P$ relatively to $SP$ is named $E_{SP}(P)$.

Note that an exact eraser is always strict. Let $P(SK)$ be the set of all subsets of the set of keywords $SK$. We consider the set $ER(SK)$ of all erasers of all sets in $P(SK)$.

The idea to limit the set of negative keywords is to replace subsets of negative keywords of a given $C_i$ campaign by a set of smaller cardinal of large erasers, but which are not erasers of the $sk_i$ keywords that $C_i$ must not filter. Those erasers, as they are large, may filter many more keywords that would have been filtered by the initial list. But this is no issue since the additional keywords erased will either be accepted by another $C_j$ campaign, either be accepted by a higher priority campaign $C_2$ or $C_1$.

The problem becomes informally to balance the set of keyword in about $\sqrt{n}$ groups of size of more or less $\sqrt{n}$ keywords using the minimum of large or exact erasers. Figure 7 shows the initial state. One approach we tested to reach this goal is to:

1. filter erasers by image size and only keep those which image is less than or equal to $\sqrt{n}$ (see Figure 8a).
2. select as few erasers as possible to cover $SK$ with non-overlapping images (see Figure 8b).
3. group remaining erasers together to merge their images to form larger images but still of size less than or equal to $\sqrt{n}$ (see Figure 8c).

Step 2 is a classical problem called exact weighted set packing which is NP hard. However, there does not exist a standard guaranteed heuristic to approximate it.

We propose an heuristic based on a weighted graph coloring. We define the graph $GE$ as follows: its vertices are the set of all large erasers of image sizes less than $\sqrt{n}$. Let $E_1$ and $E_2$ be two erasers. There is an arc $(E_1, E_2)$ in $GE$ if the images of $E_1$ and $E_2$ intersect. The two erasers are then said incompatible. Each eraser node $E$ is weighted by $I(E)$. We use Welsh-Powell heuristic [4] which returns a color for each node $E$, denoted $c(E)$. For each such color, we sum all images of all nodes colored the same and we select the color $c$ leading to the maximum such sum. We then compute the union of all images of all eraser nodes colored $c$:

$$SC = \bigcup_{E: c(E) = c} I(E).$$

Eventually, for each keyword in $P \setminus SC$, we add the keyword as its own exact eraser. The remaining set of erasers $SE$ is thus:

$$SE = \{ E \mid c(E) = c \text{ (large)} \} \cup SC \setminus P \text{ (exact)}$$

We define two algorithms: reduce($S$) where $S$ is a set of keywords, which returns a set of erasers $ES$, large or exact of $S$. We also define expand($ES$) which returns the original set $S$.

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**Fig. 7:** Exact and large erasers of a set of keywords $SK$. A keyword is drawn as a circle while an eraser as a black square.
Fig. 8: Scheme of our approach to balance the set of keywords in about $\sqrt{n} = 3$ groups of size of more or less $\sqrt{n} = 3$ keywords using the minimum of large or exact erasers.

4.1 Experimental Results

We performed some tests on real data for 2 marchant sites, with 3000 rules for the first site and 7000 for the second. The following table shows our results, in which we also exhibit the number of erasers (neras) in our intersection graph and its number of transitions (ntrans).

| Name  | SK | mm | NK | neras  | ntrans | h/heuristic | h/neras |
|-------|----|----|----|--------|--------|-------------|---------|
| Site2 | 1000 | 1 | 0 | 63246 | 22332 | 908790 | 18193 | 0.29 |
| Site2 | 2000 | 1 | 0 | 178886 | 39732 | 1705080 | 44215 | 0.25 |
| Site2 | 3000 | 1 | 0 | 328634 | 56989 | 2530764 | 85639 | 0.26 |
| Site2 | 4000 | 1 | 0 | 505965 | 71969 | 3249978 | 127334 | 0.25 |
| Site2 | 5000 | 1 | 0 | 707107 | 84299 | 3856870 | 169946 | 0.24 |
| Site2 | 6000 | 1 | 0 | 929516 | 96588 | 4424679 | 227781 | 0.24 |
| Site2 | 7000 | 1 | 0 | 1111324 | 107003 | 5038870 | 290702 | 0.25 |

| Site1 | 1000 | 100 | 30 | 74254 | 2653 | 23110 | 20993 | 0.28 |
| Site1 | 2000 | 100 | 30 | 190287 | 4763 | 42748 | 56155 | 0.29 |
| Site1 | 3000 | 100 | 30 | 340337 | 7123 | 68661 | 118187 | 0.35 |

Our tests remain succint, and we observe roughly a reduction (column h/neras) of about $\frac{2}{3}$ of the number of negative keywords required to organise the shopping account. We plan however to develop more tests and study more parameters, like the size of the graph of eraser intersections compared to the distinct word number and the maximal number of words in a keyword in the entry set.

5 Updates

The structure must allow to optionally update the merchant stream easily. More specifically, a user must be able to:

- op1: add a rule $R^c_1 : \text{key-add} \mid CPC1 \Rightarrow I = \{Item_1, Item_2, \ldots, Item_k\}$
- op2: remove a rule on existing items $R^c_2 : \text{key-rm} \mid CPC2 \Rightarrow I = \{Item_1, Item_2, \ldots, Item_k\}$
- op3: remove an item $\text{Item-rm}$ and remove/slit all rules associated with it.

The idea is to update smoothly the structure, touch as few AdGroup as possible, until the campaign becomes too unbalanced. Only then a large update is performed.
5.1 op1: Add A Rule

There exist many possible strategies to add a rule on existing items, with possibly distinct objectives. For instance, one objective is possibly that the structure remains meaningful for an account manager, or a client. Another objective can be to minimize the number of AdGroups touched. A third objective is to globally minimize the number of negative keywords. We propose an algorithm for this last goal below. Two cases might occur:

1. there exists a set \( \{ i_1 \ldots i_k \} \) such that \( 1 \leq j \leq k, \quad Neg(C^j_3) \) does not erase \( \text{key-add} \). Then let \( 1 \leq l \leq k, \) be the indice such that \( |sk_i| \) is minimal. Then, (a) let \( sk_i \leftarrow sk_i \cup \{ \text{key-add} \} \), (b) for all \( 1 \leq j \leq k, j \neq l, \quad Neg(C^j_3) \leftarrow Neg(C^j_3) \cup \text{key-add} \). Then, in \( C^l_3 \), (c) for each AdGroup ad in \( C^l_3 \), \( Neg(ad) \leftarrow \text{key-add} \), and eventually we create in \( C^l_3 \) a new AdGroup \( adnew \) and set

\[
Neg(adnew) \leftarrow sk_i \setminus \text{key-add}.
\]

2. all \( Neg(C^l_3) \) erase \( \text{key-add} \). There are two main possible strategies:

(a) either modify the negative set of one of the \( C_3 \) campaign not to filter \( \text{key-add} \) anymore, and then apply point 1. We discuss this approach below.

(b) either create a new \( C^l_3 \) campaign, setting \( Neg(C^l_3) \leftarrow SK \). In this campaign we create a single

AdGroup \( adnew \).

Point 2-(a) requires a specific algorithm. After the reduction of the number of negatives using the heuristic of Section 4, large erasers permit to lower the number of exact negatives, but exact negatives can always remain a last option if erasers are too large and erase the new keyword \( \text{key-add} \) we need to add. Thus, the approach is to identify which group \( sk_i \cup \text{key-add} \) leads to the minimum increase of the negative erasers of all \( C_3 \).

5.2 op2: Remove A Rule On Existing Items

Removing a rule is not difficult, roughly it suffices to remove \( \text{key-\text{rm}} \) for each negative set of all campaigns it belongs to.

5.3 op3: Remove An Item With Rules Associated With It

To remove a specific item, it suffices to remove each rule where the item is the only target of the rule.

6 Larger Example Of \( C_3 \) Campaigns

\[
\begin{align*}
\text{nike shoes} \models CPC1 & \Rightarrow \text{Item}_1 & \text{large tee-shirt} \models CPC2 & \Rightarrow \text{Item}_2, \text{Item}_3 \\
\text{garmin chronometer} \models CPC3 & \Rightarrow \text{Item}_4 & \text{adidas running shoes} \models CPC4 & \Rightarrow \text{Item}_5 \\
\text{nike soccer white} \models CPC5 & \Rightarrow \text{Item}_6 & \text{soccer colored mens} \models CPC6 & \Rightarrow \text{Item}_1 \\
\text{adidas superstar} \models CPC7 & \Rightarrow \text{Item}_7 & \text{adidas superstar sneaker} \models CPC8 & \Rightarrow \text{Item}_5 \\
\text{large superstar shoes} \models CPC9 & \Rightarrow \text{Item}_2 & \text{nike air max} \models CPC10 & \Rightarrow \text{Item}_2 \\
\text{air max} \models CPC11 & \Rightarrow \text{Item}_2 \\
\end{align*}
\]

The large erasers with an image size strictly greater than one are the following:

\[
\begin{align*}
\text{large erasers} & \quad \text{image} \\
\{\text{nike}\} & \quad \text{nike shoes, nike soccer white, nike air max} \\
\{\text{shoes}\} & \quad \text{nike shoes, adidas running shoes, superstar shoes} \\
\{\text{large}\} & \quad \text{large tee-shirt, large superstar shoes} \\
\{\text{air}\} & \quad \text{nike air max, air max} \\
\{\text{max}\} & \quad \text{nike air max, air max} \\
\{\text{adidas}\} & \quad \text{adidas running shoes, adidas superstar, adidas superstar sneaker} \\
\{\text{adidas, superstar}\} & \quad \text{adidas superstar, adidas superstar sneaker} \\
\{\text{soccer}\} & \quad \text{nike soccer white, soccer colored mens} \\
\{\text{superstar}\} & \quad \text{adidas superstar, adidas superstar sneaker, large superstar shoes} \\
\end{align*}
\]

All image sizes of all large erasers are of size less than \( \sqrt{11} \geq 3 \), thus we keep all those erasers and build the graph \( GE \), given in figure 9.
We thus split $SK$ in 3 groups $sk_1 = \{\text{nike shoes, nike soccer white, nike air max}\}$, $sk_2 = \{\text{adidas running shoes, adidas superstar, adidas superstar sneaker}\}$ and $sk_3 = \{\text{large superstar shoes, air max, large tee-shirt, garmin chronometer}\}$.

The erasers of $sk_1, sk_2$ and $sk_3$ are respectively $\{\text{nike(large)}\}$, $\{\text{adidas(large)}\}$ and $\{\text{large(large)}, \text{air max(exact), garmin chronometer(exact)}\}$.

We create 3 AdGroups for the first $C^3_1$ campaign:

- $\text{AdGroup}_1(C^3_1)$ corresponds to $\text{nike shoes}$, and $\text{Neg(AdGroup}_1(C^3_1)) = \{\text{nike soccer white, nike air max}\}$.
- $\text{AdGroup}_2(C^3_1)$ corresponds to $\text{nike soccer white}$, and $\text{Neg(AdGroup}_2(C^3_1)) = \{\text{nike shoes, nike air max}\}$.
- $\text{AdGroup}_3(C^3_1)$ corresponds to $\text{nike air max}$, and $\text{Neg(AdGroup}_3(C^3_1)) = \{\text{nike shoes, nike soccer white}\}$.

The remaining AdGroups of $C^2_3$ and $C^3_3$ are built the same way.

### 6.1 Adding A Rule (op1)

Let us illustrate the procedure to add a rule. We present two examples, a simple and a more complex one. First, let us add the rule

1. $\text{nike jogging} \models \text{CPC12} \Rightarrow \text{Item}_6$

   The keyword $\text{nike jogging}$ is accepted only by $C^1_3$ and erased by the others. This is the simplest case, we add $\text{nike jogging}$ to $C^1_3$, create a new adgroup $\text{AdGroup}_4(C^1_3)$ that corresponds to $\text{nike jogging}$, and add the eraser $\text{jogging}$ to the negative set of all the others AdGroups of $C^1_3$.

We now add the rule

1. $\text{nike large shoes} \models \text{CPC13} \Rightarrow \text{Item}_1$

   The keyword $\text{nike large shoes}$ is erased by all low level campaigns $C^1_3, C^2_3, C^3_3$. Thus there are several possibilities, as stated in Section 5.1, depending of our goal. If the goal is to minimize the number of adgroup changes, a simple solution (point 2-(b) in Section 5.1) is to create a new campaign $C^4_3$ for the new keyword. The negative keywords of $C^4_3$ have to stop all the other keywords excepted $\text{nike large shoes}$. A possibility is $\text{Neg}(C^4_3) = \{\text{nike shoes(exact), tee-shirt(large), garmin(large), air(large), adidas(large), soccer(large), superstar(large)}\}$.

### 7 Perspectives

We plan to implement this theoretical approach in a real shopping account and then measure the volume modifications on which at this development state of our technique we have only a restricted visibility. We are convinced that the notion of keyword $\text{eraser}$ and its associated algorithmics is just at its beginning.
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