Internal mesh optimization
Semantic linking and siloing
Big data

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Cdiscount

Plan

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1. Introduction

Objective : give you an overview of the meshing optimization done at Cdiscount, the first french e-commerce web site

- Heuristic based optimization algorithm to push specific products
- An e-commerce pitch
- Semantic similarity and constraining for shrinking our universe
- Big data implementation

2. Heuristic

Some notations

Let $N \in \mathbb{N}$ be the number of nodes in our mesh.

Let $(X_i)_{i\in\{1,\ldots,N\}}$ be the vertices (URLs) of our oriented graph.

Let $(G_{ij}) \in \{0,1\}^{N\times N}$ be the adjacency matrix of our oriented graph.

Let here define f, a given data per URL, which gives a potentiality metrics for our vertices.

$$\begin{array}{cccc} f & : & (X_i)_{i\in\{1,\ldots,N\}} & \rightarrow & \mathbb{R}^+ \\ & & x & \mapsto & f(x) \end{array} \quad (1)$$

In-rank

We restrain the universe to our site where we compute the standard page-rank.

Initialization :

$$\forall u \; PR(u) = \frac{1}{N} \tag{2}$$

Iterative computation :

$$PR(u) = \frac{(1-c)}{N} + c \times \sum_{v \to u} \frac{PR(v)}{card(\{v \to u\})} \tag{3}$$

Our heuristic

We want here to optimize the adequacy of our mesh (X_i) to our potentiality vector f. We here postulate the following heuristic to assess the relevance of a mesh :

$$\max_{(G_{ij})\in\{0,1\}^{N\times N}} \left\{ \sum_{i=1}^{N} trafic\,(X_i) \times pageRank(X_i) \right\} \tag{4}$$

3. Metaheuristics

Exhaustive brute force doesn't work

For a $N = 10^6$ millions URLs web site, we have 2^{N^2} with a 2048 bits mantissa, 256 bits exponent

$2^{10^{6^2}} =$

9.5762442314927432848050594956989483747127095675192905698213128517073583274396016675898

7147051841431464684537524428064846905611699754984150157774926559473752701594766514 18975

3007076585475688023533848794198035747309524801977743805520406627581276095713336837 03207

9100702470481944595046869861247864923533875503184952416215722719251272882739937877 78380

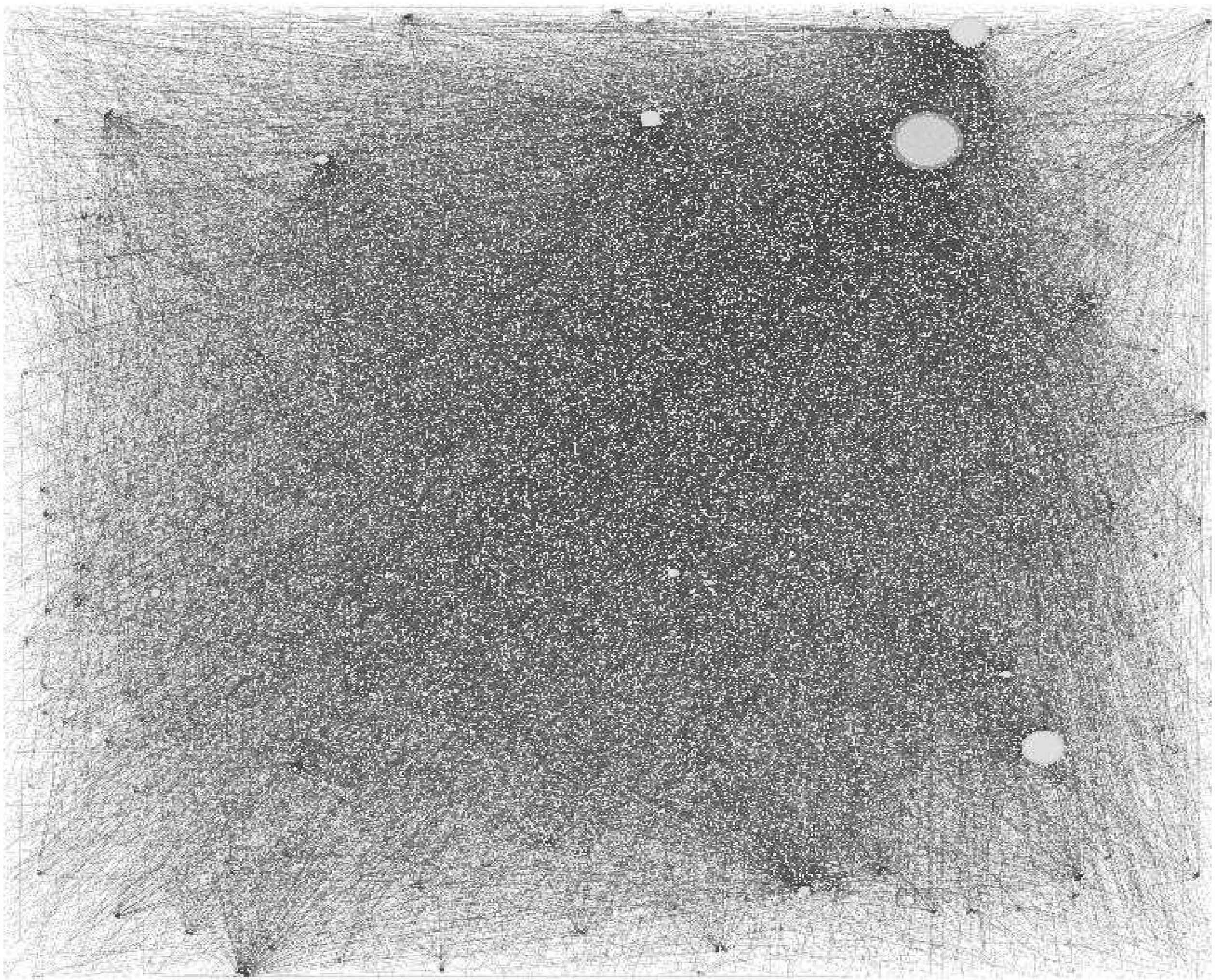
4507748096113958101914173634018890387571822794840192038701774133181130739114184636 15759

6479775384785601669589887210486878542801872836619259375300172434611459055738023144 71888

4917587571626776840174245970144334181791152894635526307518965593122136244706174533 25056

5836008e+301029995663

Picturing our smallest store : jewelery



Metaheuristics

We here have to maximize over all possible graphs. We have to find a clever global optimization methodology : metaheuristics such as global search, multistart, particle swarm, simulated annealing or genetic algorithm are all good candidates.

What a genetic algorithm

- Genetic algorithm mimics evolutionary biology to find approximate solutions to optimization problems
- Start with an initial generation of candidate solutions that are tested against the objective function (fitness of the individual)
- Subsequent generations evolve from the first through selection, crossover and mutation
- The individual that best minimizes the given objective is returned as the ideal solution

Why a genetic algorithm

- Lots of local minima to avoid
- Non continuous universe, constraints and objective
- Problem with noise and non-smooth data

Cleverly evolving through our universe

Child spawning from 2 parents crossover

(0 0 0 0 1 0 1 1 1 1 0 1 0)

(1 1 0 1 1 0 1 1 1 1 1 0 0)

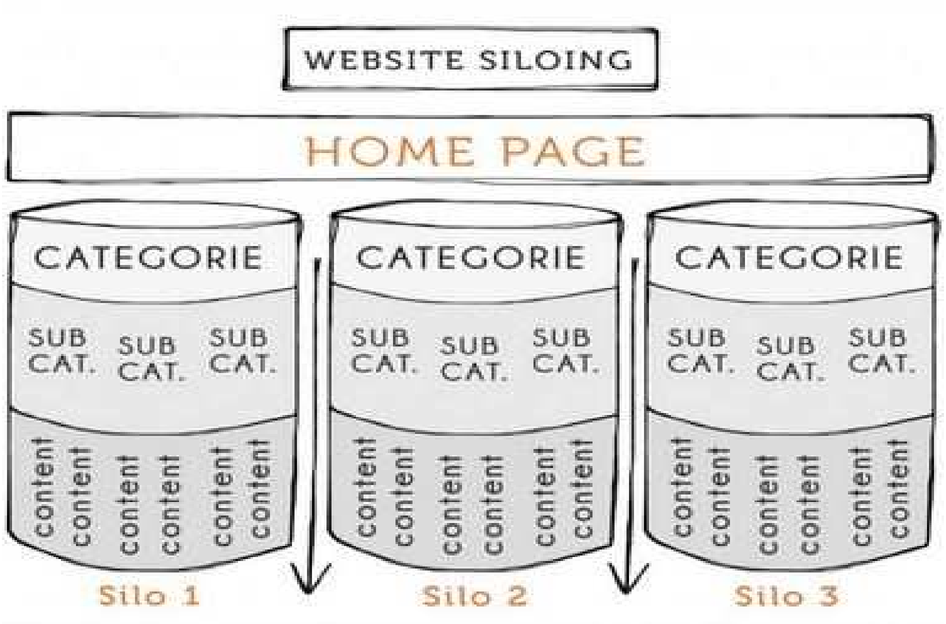
(* * 0 * 1 0 1 1 1 1 * * 0)

Mutation of an individual

(1 1 0 * 1 0 1 1 * 1 1 0 0)

4. Shrinking our universe with siloing and semantic similarity

Siloing and links categorizing



metalist1/metalist2 metalist1/list1

(001010 .. 00110 ..... 10100)

Semantic similarity

We slack our universe by allowing links only between semantically similar URLs :

$$\max_{(G_{ij})\in\{0,1\}^{N\times N}\ G_{ij}=0\ if\ CS(ij)\leq t} \left\{ \sum_{i=1}^{N} f\left(X_i\right) \times PR(X_i) \right\} \tag{5}$$

where $CS(ij)$ is a semantic distance between the two linked pages i and j. $CS(ij)$ can be defined very easily as the scalar product of the tf/idf vectors of the product descriptions whose weight are defined by the well known formula :

$$w_{ik} = \frac{tf_{ik} \log\left(\frac{N}{n_k}\right)}{\sqrt{\sum_{k=1}^{t}(tf_{ik})^2 \log\left(\frac{N}{n_k}\right)^2}} \tag{6}$$

5. Same problem with an e-commerce flavor

$$\sum_{i \in Keywords} SV\,(i) \times CTR\,(position\,(i)) \times CR\,(i) \times P\,(i) \qquad (7)$$

where $position\,(i)$ is the estimated position in search engine results coming from the modification of our new mesh,

$SV\,(i)$ is the search volume for the keywords i estimated by the search engine.

and $CTR\,(i)$ is the click through rate for an URL at the position place in the search engine results.

6. Prototyping example

$$(X_i) = \{'home','metalist1','metalist2',$$

$$'list1','list2','list3','list4',$$

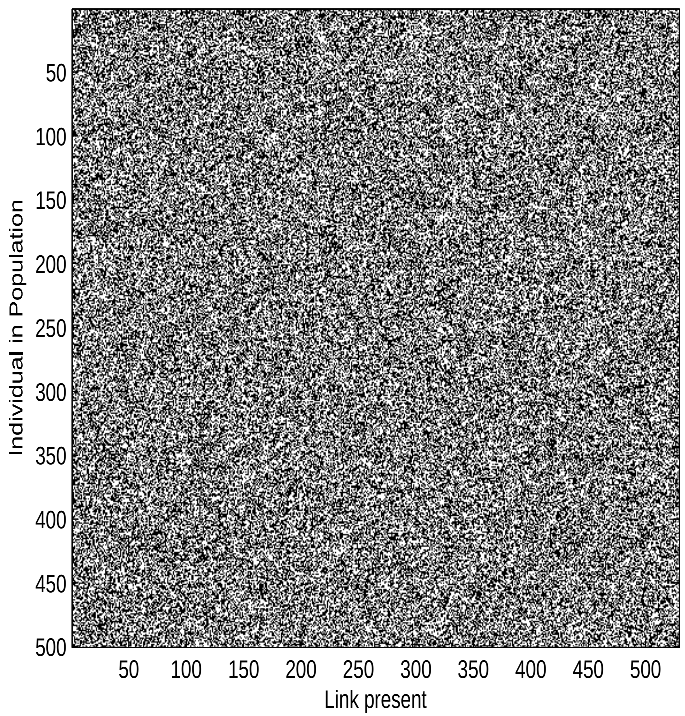
$$'product1','product2',...,'product32'\};$$

$$f\,(X_i) = [100; 80; 55;$$

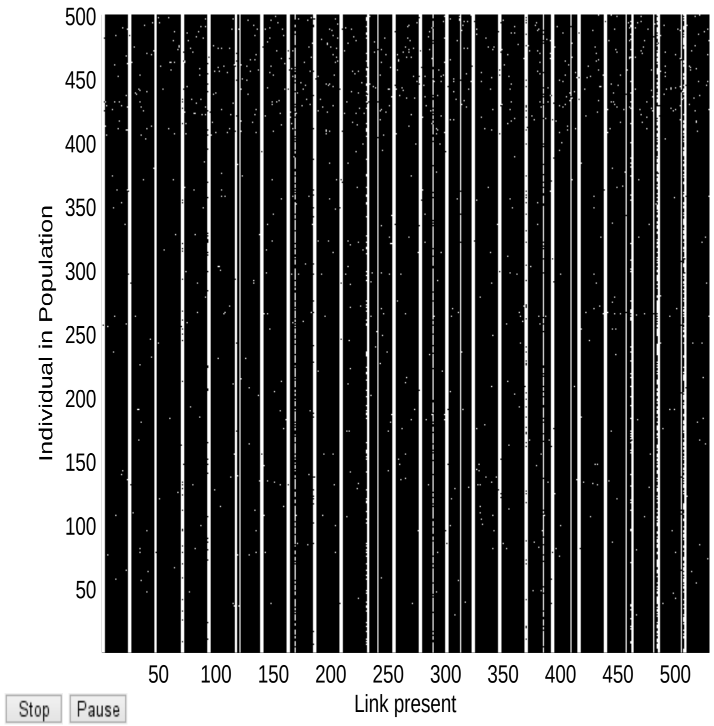
$$40; 35; 25; 20;$$

$$4; 5; ...; 3]$$

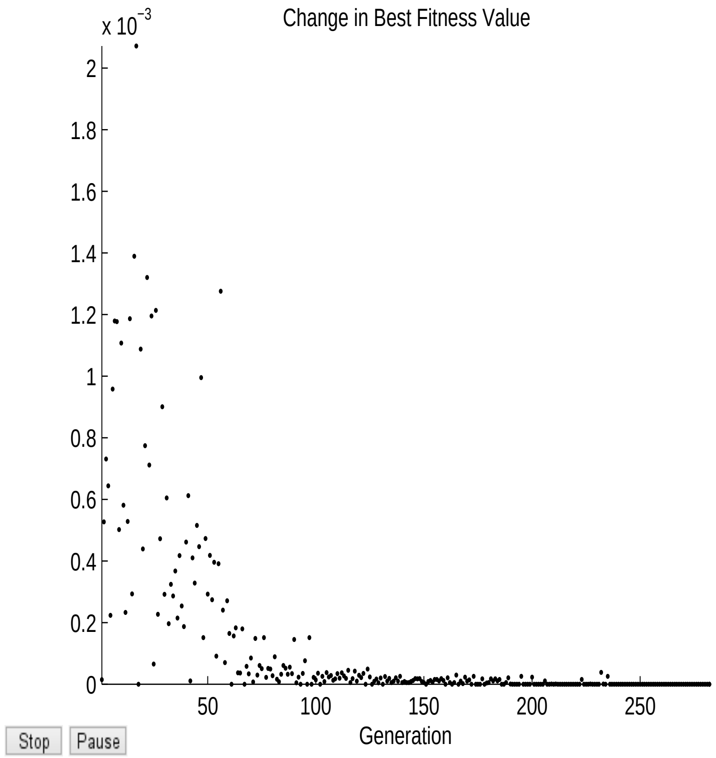
Initial population



Population at convergence

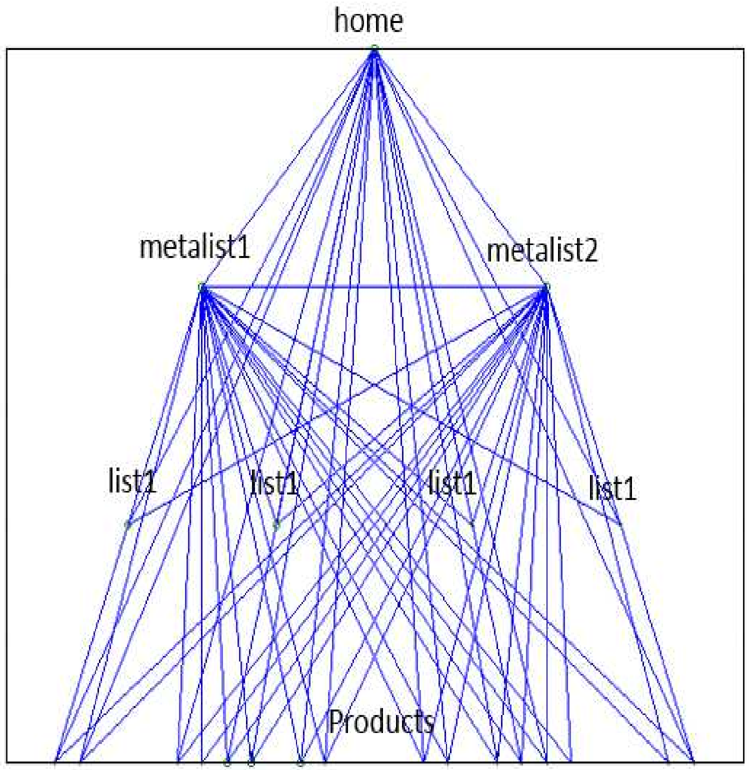


Best chromosome fitness function evolution



The structure found is as we expected arborescent : home linking to metalists, metalists linking to lists and lists to products.

Optimal site structure


home
metalist1
metalist2
list1
list1
list1
list1
Products

7. Big data implementation : Neo4j and Spark GraphX