Internal mesh optimization
Semantic linking and siloing
Big data

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Plan

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1. 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.

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

$$f(X_i) = PR_{ext}(X_i) + \epsilon(X_i) \tag{2}$$

In-rank

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

Initialization :

$$\forall u \, PR(u) = \frac{1}{N} \tag{3}$$

Iterative computation :

$$PR(u) = \frac{(1-c)}{N} + c \times \sum_{v \to u} \frac{PR(v)}{card(\{v \to u\})} \tag{4}$$

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 :

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

2. 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

714705184143146468453752442806484690561169975498415015777492655947375270159476651418975

300707658547568802353384879419803574730952480197774380552040662758127609571333683703207

910070247048194459504686986124786492353387550318495241621572271925127288273993787778380

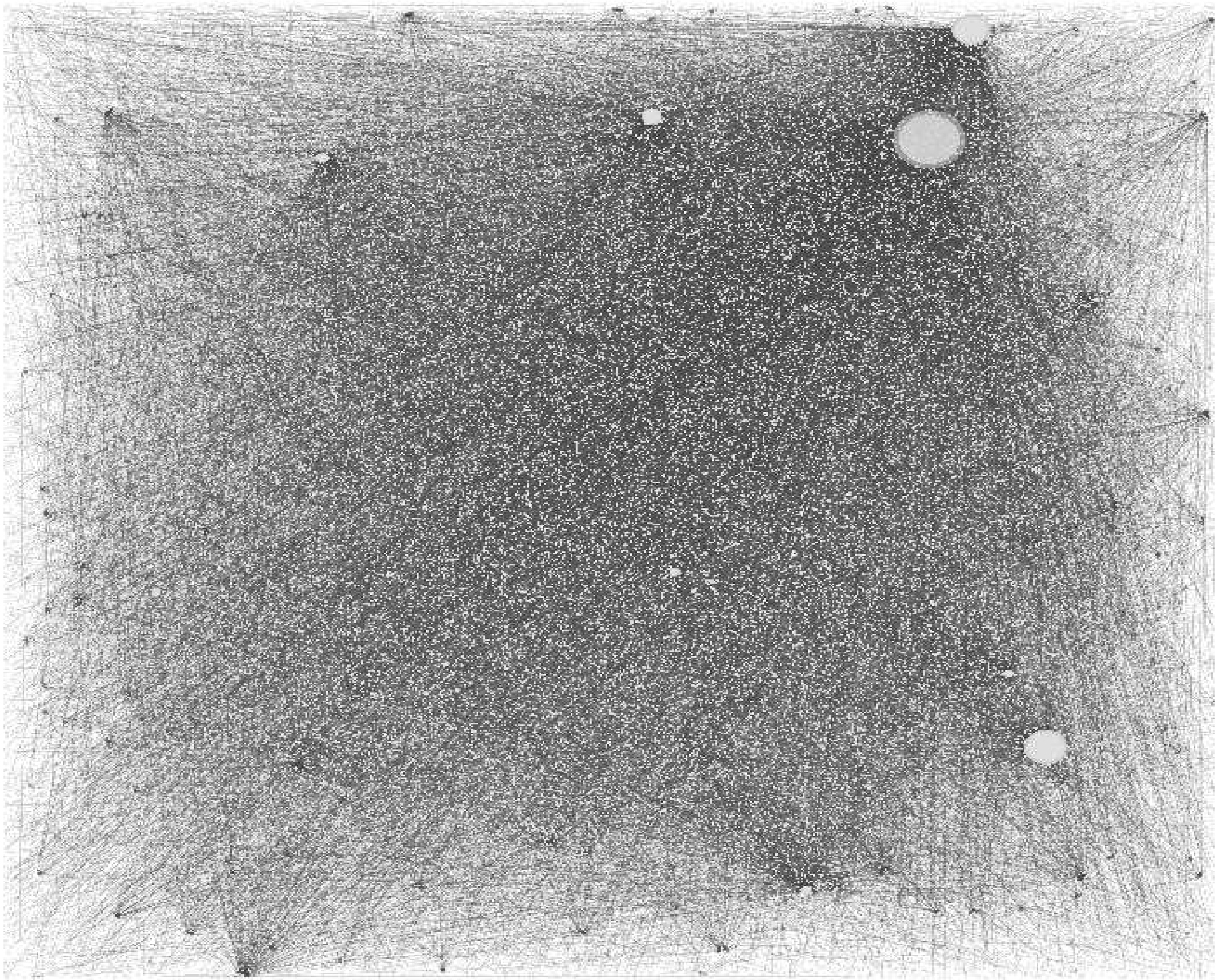
450774809611395810191417363401889038757182279484019203870177413318113073911418463615759

647977538478560166958988721048687854280187283661925937530017243461145905573802314471888

491758757162677684017424597014433418179115289463552630751896559312213624470617453325056

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 is 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 objecive 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)

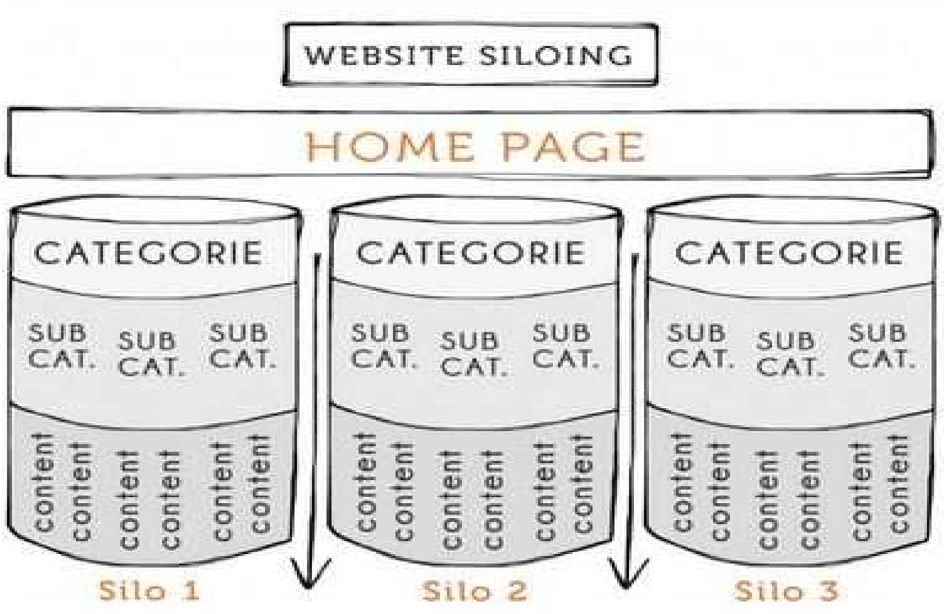
(* * 0 * 1 0 1 1 1 1 * * 0)

Mutation of an individual

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

3. 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 :

$$\max_{(G_{ij})\in\{0,1\}^{N\times N}\ G_{ij}=0\ if\ CS(ij)\leq t} \left\{ \sum_{i=1}^{N} f\left(X_i\right) \times PR(X_i) \right\} \tag{6}$$

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 :

$$w_{ik} = \frac{tf_{ik} \log\left(\frac{N}{n_k}\right)}{\sqrt{\sum_{k=1}^{t}(tf_{ik})^2 \log\left(\frac{N}{n_k}\right)^2}} \tag{7}$$

4. Same problem with an e-commerce flavor

$$\sum_{i \in Keywords} SV\left(i\right) \times CTR\left(position\left(i\right)\right) \times PR\left(i\right) \times P\left(i\right) \qquad (8)$$

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

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

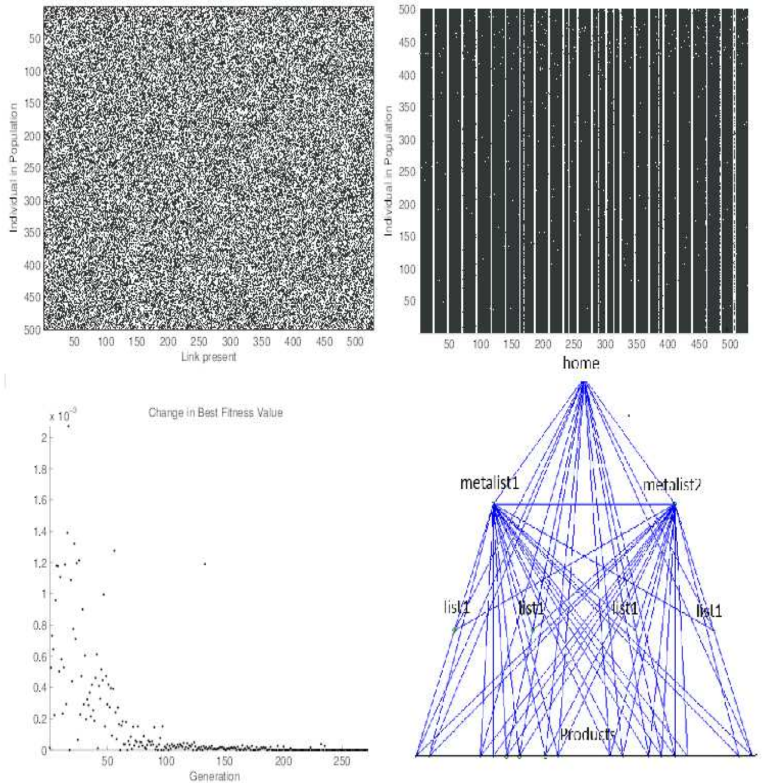
and $CTR\left(i\right)$ is the click through rate for an URL at the position place in the search engine results.

5. Prototyping example

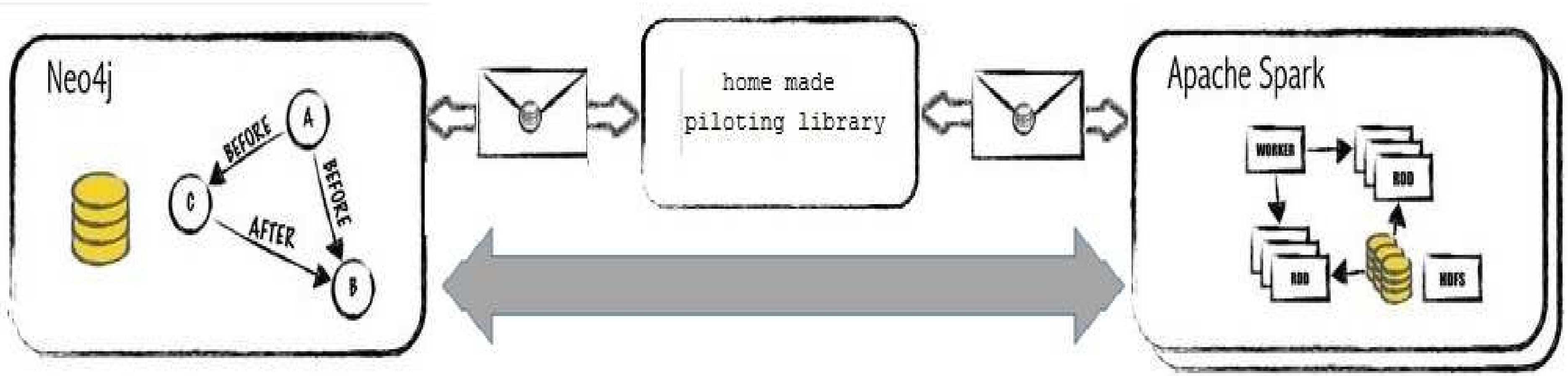
(X_i) ='home','metalist1','metalist2','list1','list2','list3','list4','product1','product2',...,'product32' ;

$f\ (X_i)$=[100, 80, 55, 40, 35, 25, 20, 4, 5,...,3] ;

Results



6. Big data implementation : Neo4j and Spark GraphX



7. Video and paper link

http ://sduprey.github.io/page_rank_optimization_video.html

http ://sduprey.github.io/article_sduprey_iswag_02_06_2015.pdf

http ://sduprey.github.io/PRESENTATION_ISWAG.pdf