Exploration adaptative de graphes sous contraintes de budget

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Scalable, Generic, and Adaptive Systems for Focused Crawling

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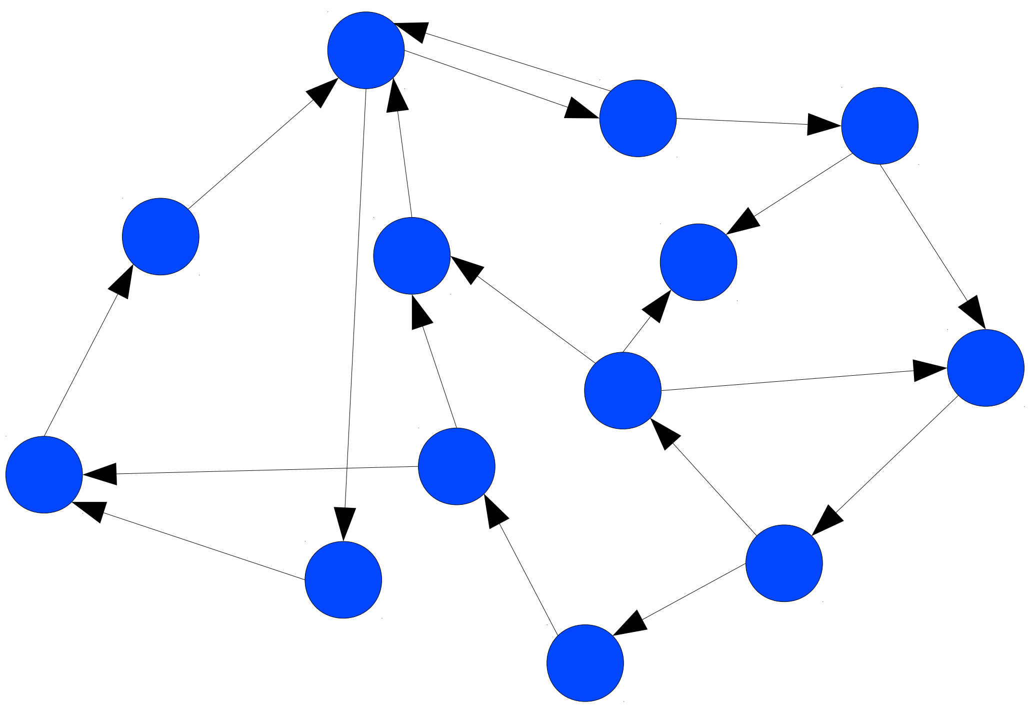
What is focused crawling?

A directed graph



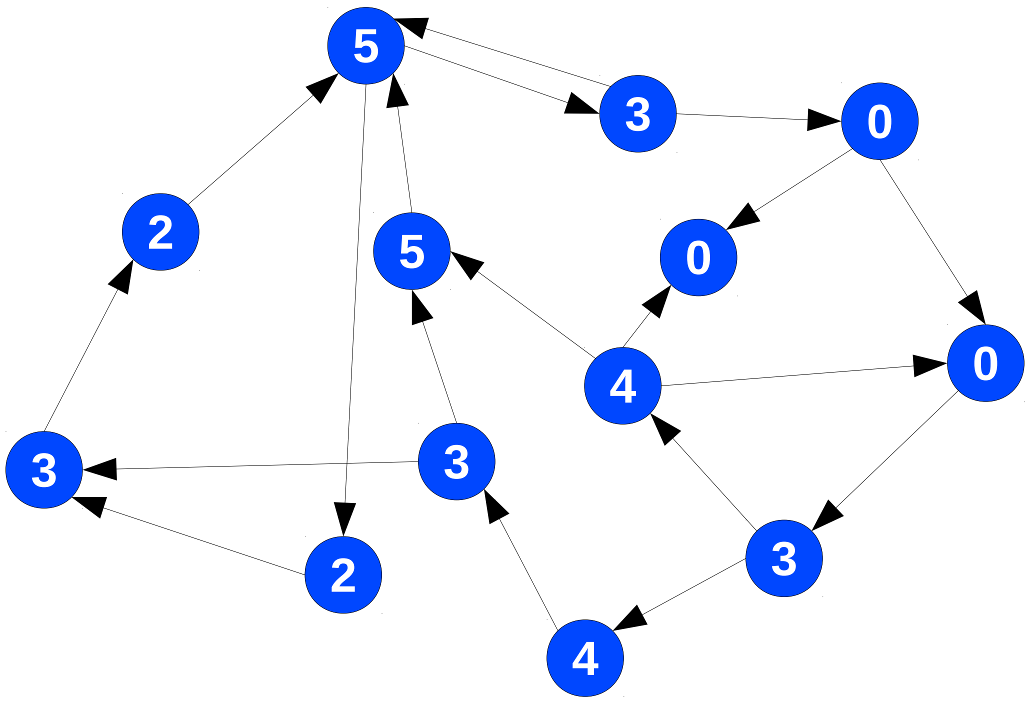
Web

Social network

P2P

etc.

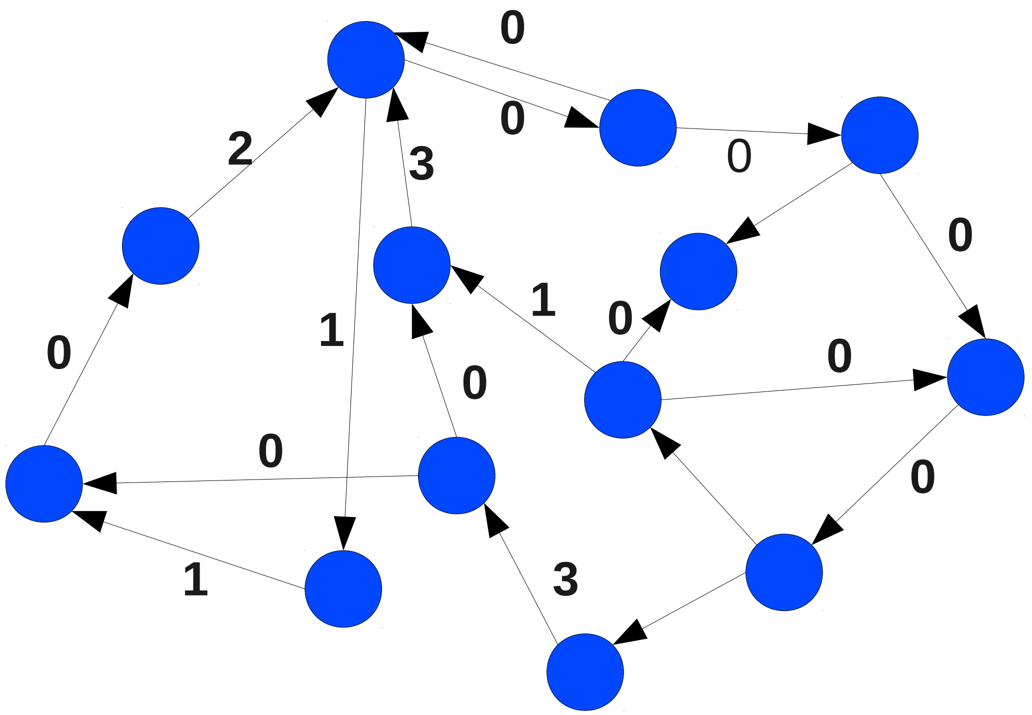
Weighted



Let *u* be a node,

$\beta(u)$ = count of the word *Bhutan* in all the tweets of u

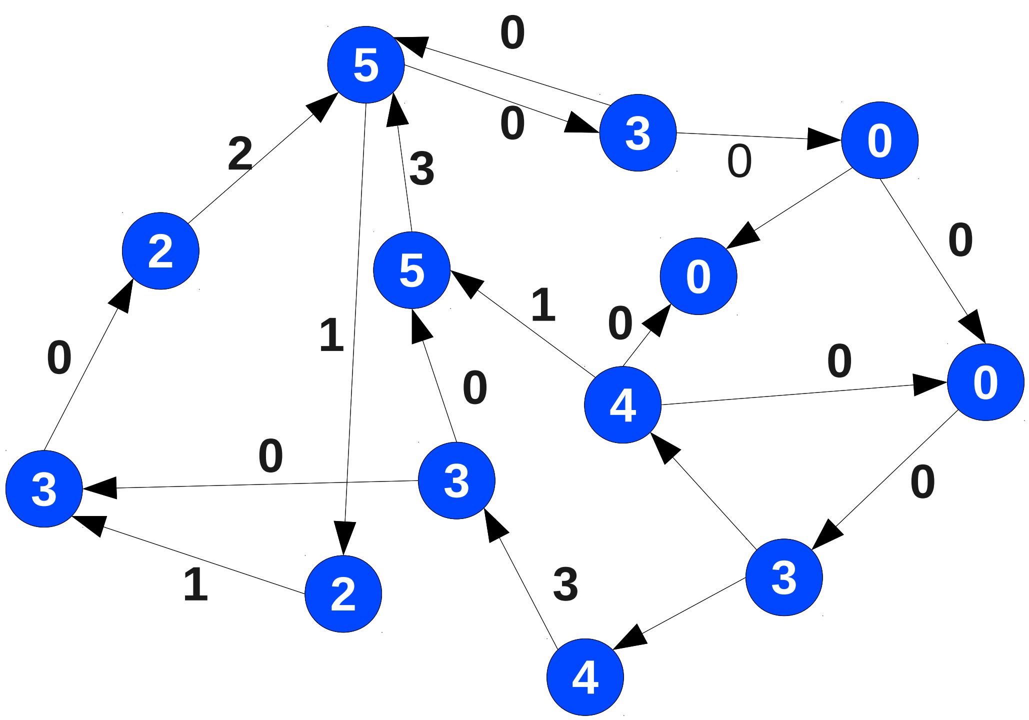
Even more weighted



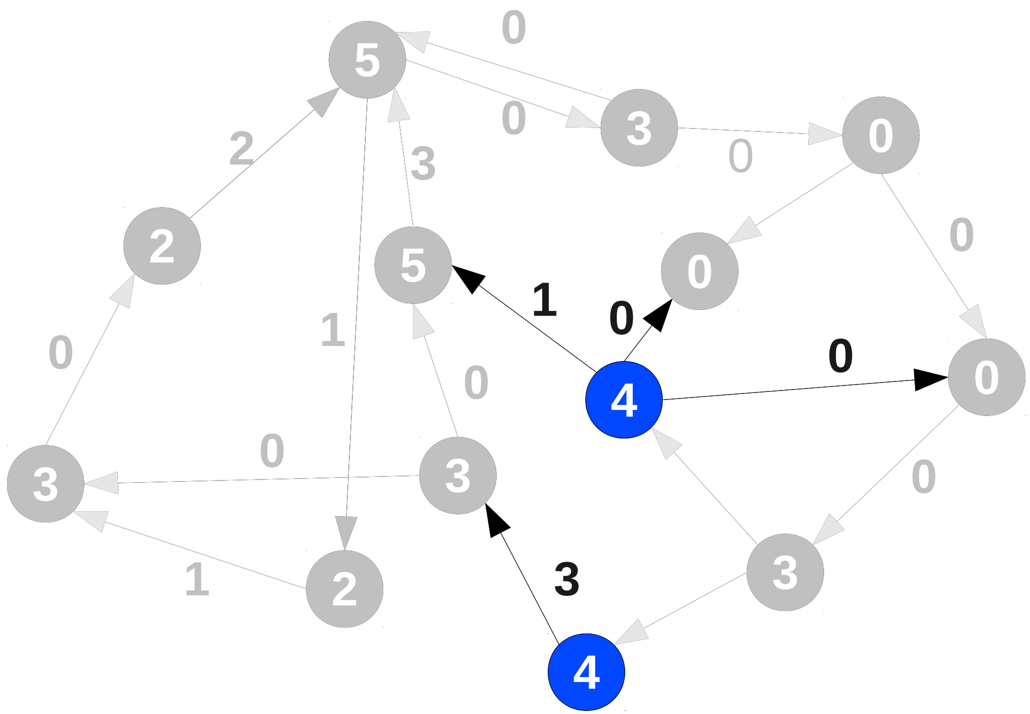
Let (u, v) be an edge,

$\alpha(u)$ = count of the word *Bhutan* in all the tweets of u mentioning v

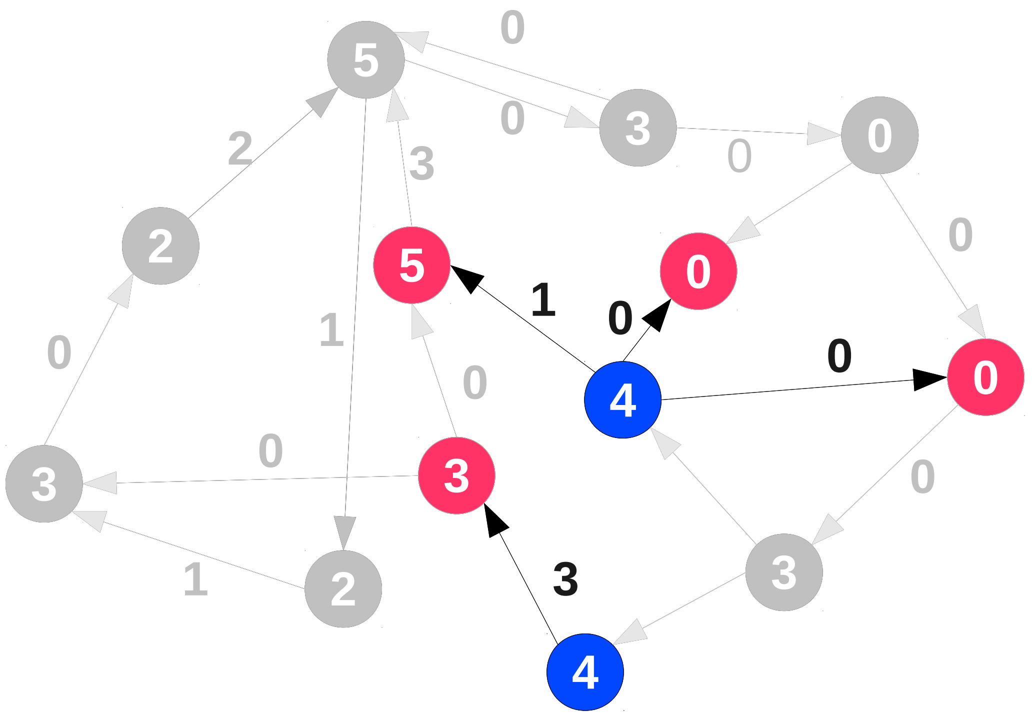
The total graph



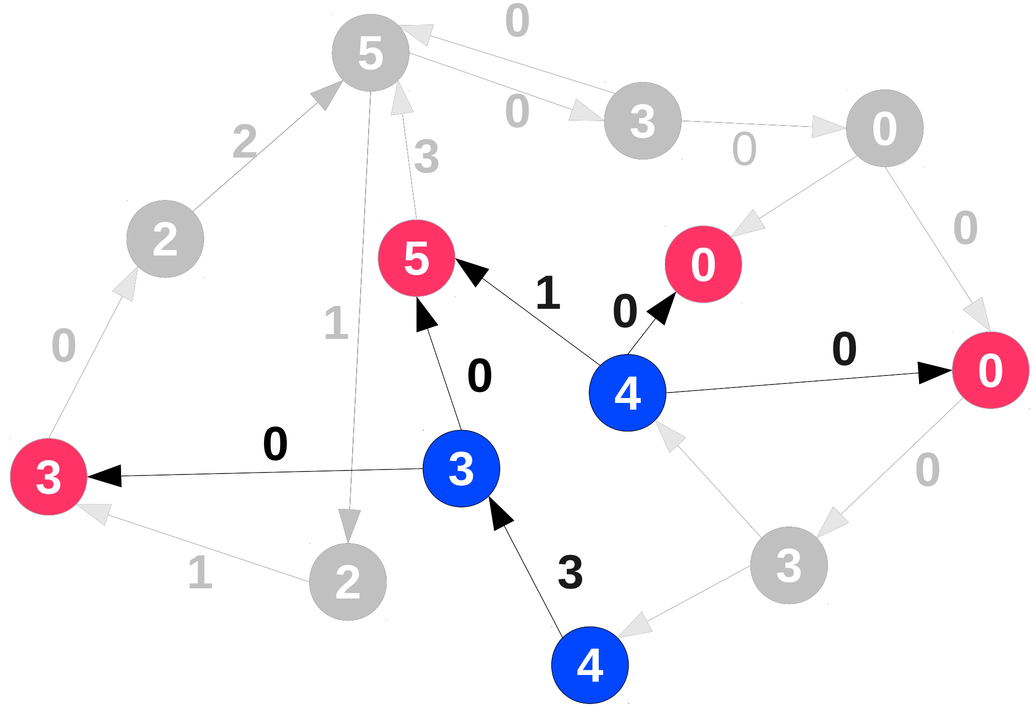
A seed list



The frontier



Crawling one node



A crawl sequence

Let V_0 be the seed list, a set of nodes,

a *crawl sequence,* starting from V_0, is

$$\{ v_i, v_i \text{ in frontier}(V_0 \cup \{v_0, v_1, .. , v_{i-1}\}) \}$$

Goal of a focused crawler

Produce crawl sequences with

global scores (sum) as high as possible

The focused crawling high-level algorithm

```
input  : seed subgraph G_0, budget n
output : crawl sequence V with a score as high as possible
V ← ();
G' ← G_0;
budgetLeft ← n;
while budgetLeft > 0 do
    frontier ← extractFrontier(G');
    scoredFrontier ←
    estimator.scoreFrontier(G', frontier);
    r ← getRefreshRate();
    NodeSequence ←
    strategy.getNextNodes(scoredFrontier, r);
    V ← (V, NodeSequence);
    for u in NodeSequence do
        G' ← G' ∪ crawlNode(u);
    budgetLeft = budgetLeft − r
return V
```

Supposing a perfect estimator

Finding an optimal crawl sequence offline:
NP-hard

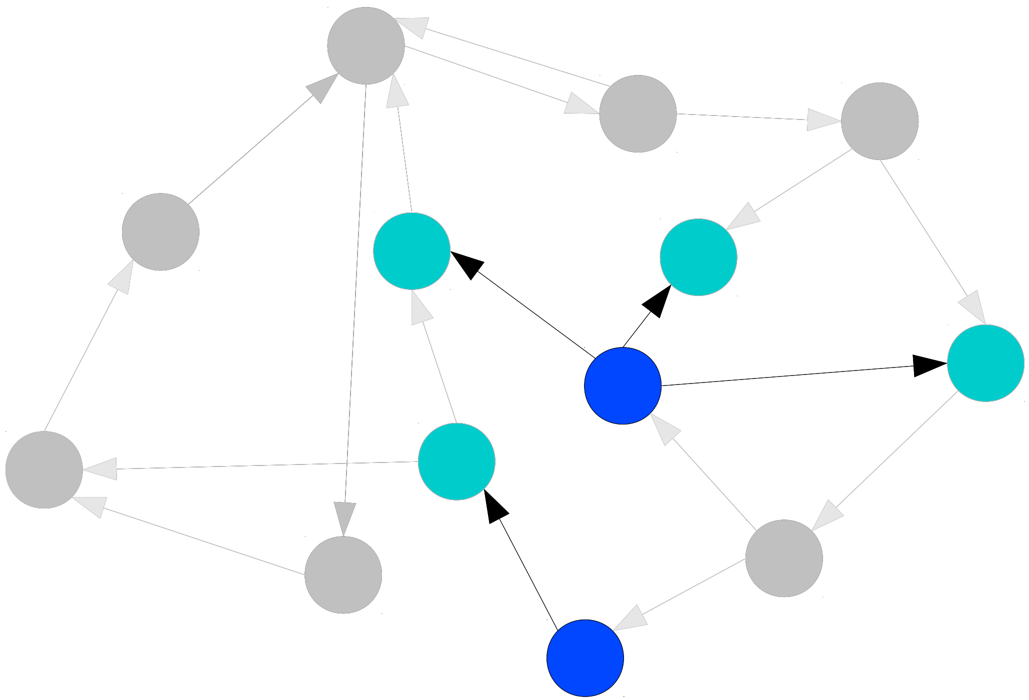
Greedy wins for a crawled graph > 1000 nodes

Refresh rate of 1 is better

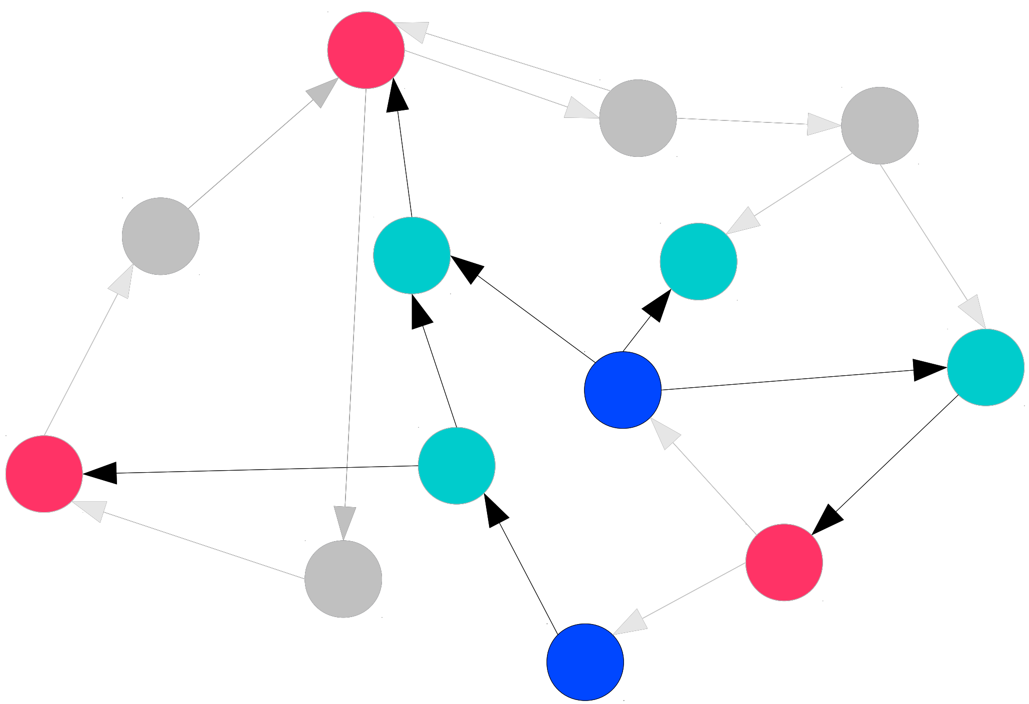
Estimation in practice

Different kinds of estimators

bfs



bfs



bfs

ESTIMATOR 1 (`bfs`). $\widetilde{\beta}(v) = \frac{1}{l(v)+1}$, *where* $l(v)$ *is the distance of* v *to* V_0.

nr

$$NR_1(v)^{t+1} = d \times w(v) + (1-d) \times avg_{(v,u)\in E'} \frac{NR_1(u)^t}{d_{\mathrm{i}}(u)}$$

$$NR_2(v)^{t+1} = d \times NR_1(v) + (1-d) \times avg_{(u,v)\in E'} \frac{NR_2(u)^t}{d_{\mathrm{o}}(u)}.$$

ESTIMATOR 2 (`nr`). $\widetilde{\beta}(v) = NR_2(v)$.

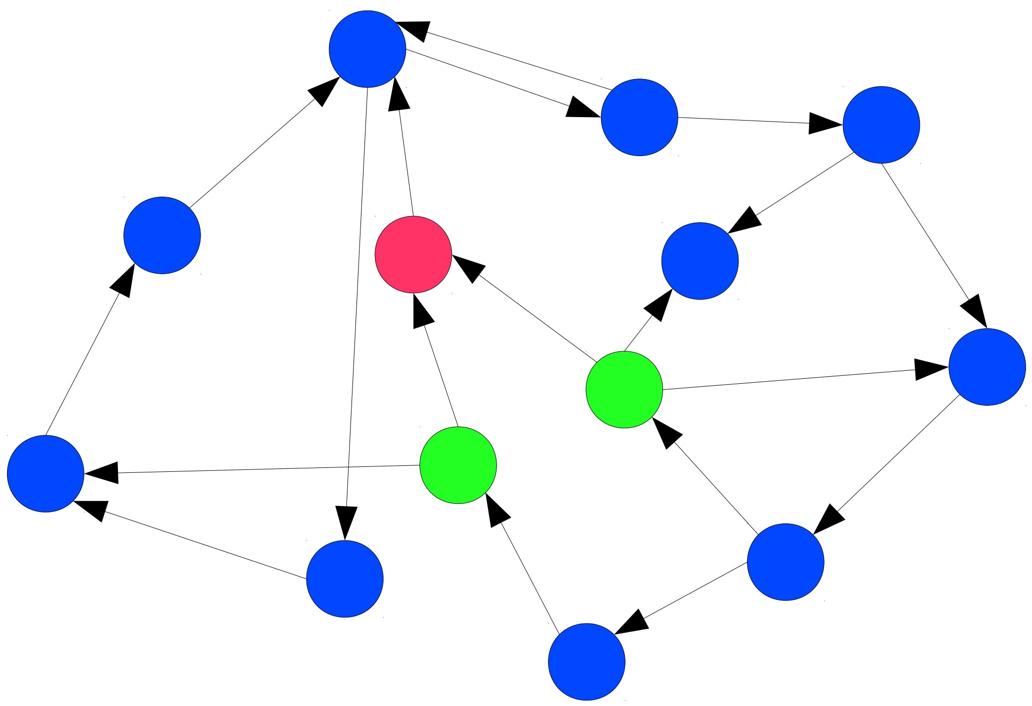
opic

1. the node v with the highest cash is selected, and its history is updated with the current cash value $H(v) = H(v) + C(v)$,
2. for each outgoing node u of v, the cash value is updated $C(u) = C(u) + \frac{C(v)}{d_{o(v)}}$,
3. the cash value of v is reset and the global counter incremented, by $G = G + C(v)$ and $C(v) = 0$.

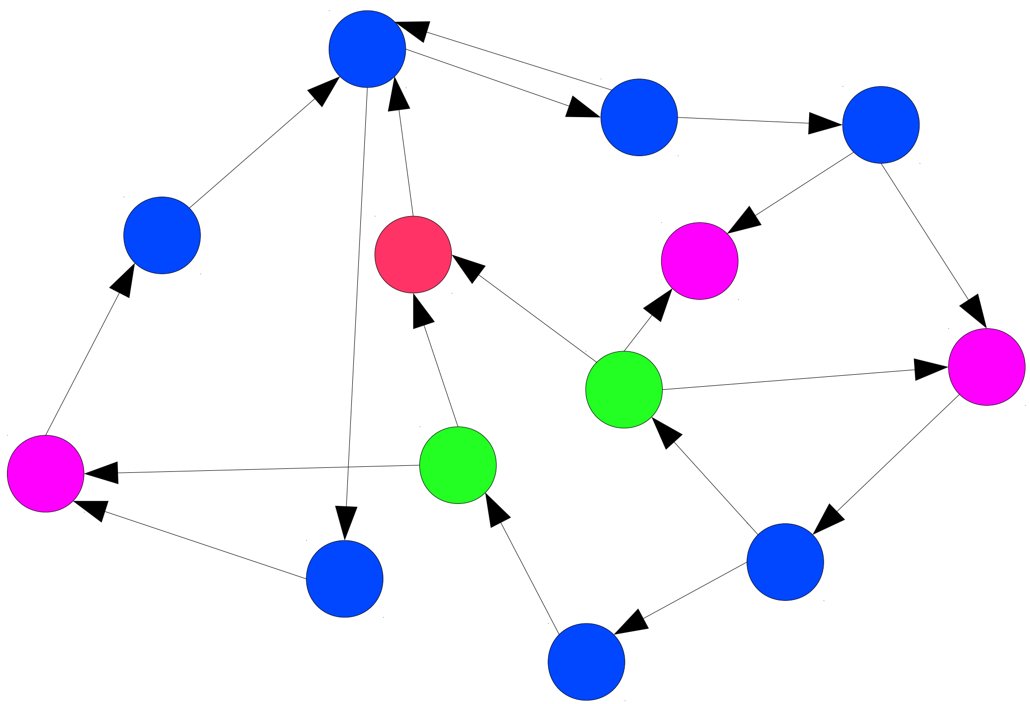
2. -> $$C(u) = C(u) + \frac{C(v)}{\sum_{(v,w)\in E'} \alpha(v,w) \times C(w)} \times \alpha(v,u) \times C(u)$$

ESTIMATOR 3 (opic). $\widetilde{\beta}(v) = \frac{H(v)+C(v)}{G+1}$.

First-level neighboorhood



Second-level neighboorhood



Neighborhood-based estimators

ESTIMATOR 4 (fl_n fl_e fl_ne sl_n sl_e sl_ne).

fl_deg: $\widetilde{\beta}(v) = d_{\mathrm{i}}(v) = |P(v)|$

fl_n: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \beta(u)$

fl_e: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \alpha(u, v)$

fl_ne: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \beta(u) \alpha(u, v)$

sl_n: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \sum_{\substack{w \in V' \\ u \in P(w)}} \beta(w)$

sl_e: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \sum_{\substack{w \in V' \\ u \in P(w)}} \alpha(u, w)$

sl_ne: $\widetilde{\beta}(v) = \sum_{u \in P(v)} \sum_{\substack{w \in V' \\ u \in P(w)}} \beta(w) \alpha(u, w)$

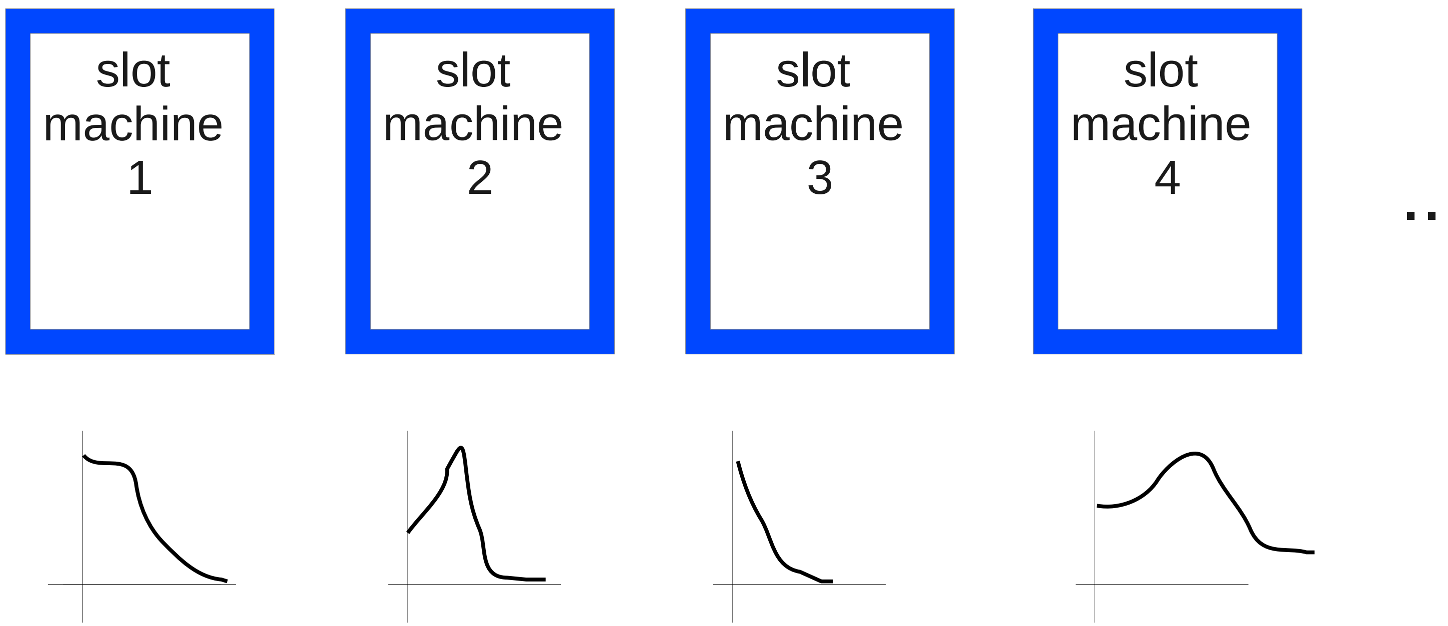
Linear regressions

ESTIMATOR 5 (lr_fl lr_sl).

lr_fl : $\widetilde{\beta}(v)$ = *trained linear combination of the* $fl\_$ *estimators.*

lr_sl : $\widetilde{\beta}(v)$ = *trained linear combination of the* $fl\_$ *and* $sl\_$ *estimators.*

Multi-armed bandits (1)



Multi-armed bandits (2)

Budget n, how to maximize the reward?

Balance exploration and exploitation

Applied to focused crawling

Slot machines: estimators

Reward: score of the top node

mab_ε

probability 1-ε: slot machine with the highest average reward

probability ε: random slot machine

ESTIMATOR 6 (mab_ε). $\widetilde{\beta}(v)$ = *output of an epsilon-greedy strategy.*

mab_ε-first

steps [0, $\lfloor \varepsilon \times N \rfloor$]: random slot machine

steps [$\lfloor \varepsilon \times N \rfloor$ +1, N]: slot machine with the highest average reward

ESTIMATOR 7 (`mab_ε-first`). $\widetilde{\beta}(v)$ = *output of an epsilon-first strategy.*

mab_var

Succession of ε-first strategies, with a reset every r steps, r varying with the context

ESTIMATOR 8 (mab_var). $\widetilde{\beta}(v)$ = *output of an epsilon-first with variable reset strategy.*

Their running times

Expected running times

Twitter API for one week:

- 3s
- 200,000 nodes

One domain website for one week:

- 1s
- 600,000 nodes

Experimental framework (1)

Dataset	Nodes (million)	Non-zero nodes (%)	Edges (million)	Non-zero edges (%)
BRETAGNE	2.2	2.0	35.6	0.5
FRANCE	"	19.2	"	6.8
HAPPY	16.9	11.0	78.0	2.4
JAZZ	"	0.6	"	0.1
WEIRD	"	3.2	"	0.4

Experimental framework (2)

--- *Graph score*

10 seed graphs

1 seed graph:
50 seeds picked randomly among non-zero β

Arithmetic average of the crawl scores (sum)

--- *Global score*

Normalization with a baseline -- *relative score*

Geometric average among the five graphs

Datasets and code are online

http://netiru.fr/research/12fc/

To measure the running times

Same crawl sequence: the oracle

Storage in RAM (20G)

3.6 GHz

The running times (ms)

Dataset	Evaluator	100	1,000	10,000	100,000
France	nr	2,832.1	19,720.5	N/A	N/A
	opic	1.9	2.5	4.6	4.7
	ne_fl	0.2	0.1	0.1	0.1
	lr_fl	0.2	0.2	0.1	0.1
	mab_var_fl	0.6	0.3	0.2	0.2
	ne_sl	8.5	27.1	2.0	6.1
	lr_sl	8.5	27.2	2.0	6.1
Happy	nr	45,965.7	105,209.3	N/A	N/A
	opic	1.8	1.6	1.9	2.5
	ne_fl	0.3	0.1	0.2	2.1
	lr_fl	0.5	0.1	0.2	2.1
	mab_var_fl	1.1	0.3	0.5	3.9
	ne_sl	111.1	24.5	63.3	240.5
	lr_sl	111.4	24.5	63.3	241.0

nr

$$NR_1(v)^{t+1} = d \times w(v) + (1-d) \times avg_{(v,u)\in E'} \frac{NR_1(u)^t}{d_\mathrm{i}(u)}$$

$$NR_2(v)^{t+1} = d \times NR_1(v) + (1-d) \times avg_{(u,v)\in E'} \frac{NR_2(u)^t}{d_\mathrm{o}(u)}.$$

ESTIMATOR 2 (nr). $\widetilde{\beta}(v) = NR_2(v)$.

Quadratic complexity, with important multipliers

Their precision

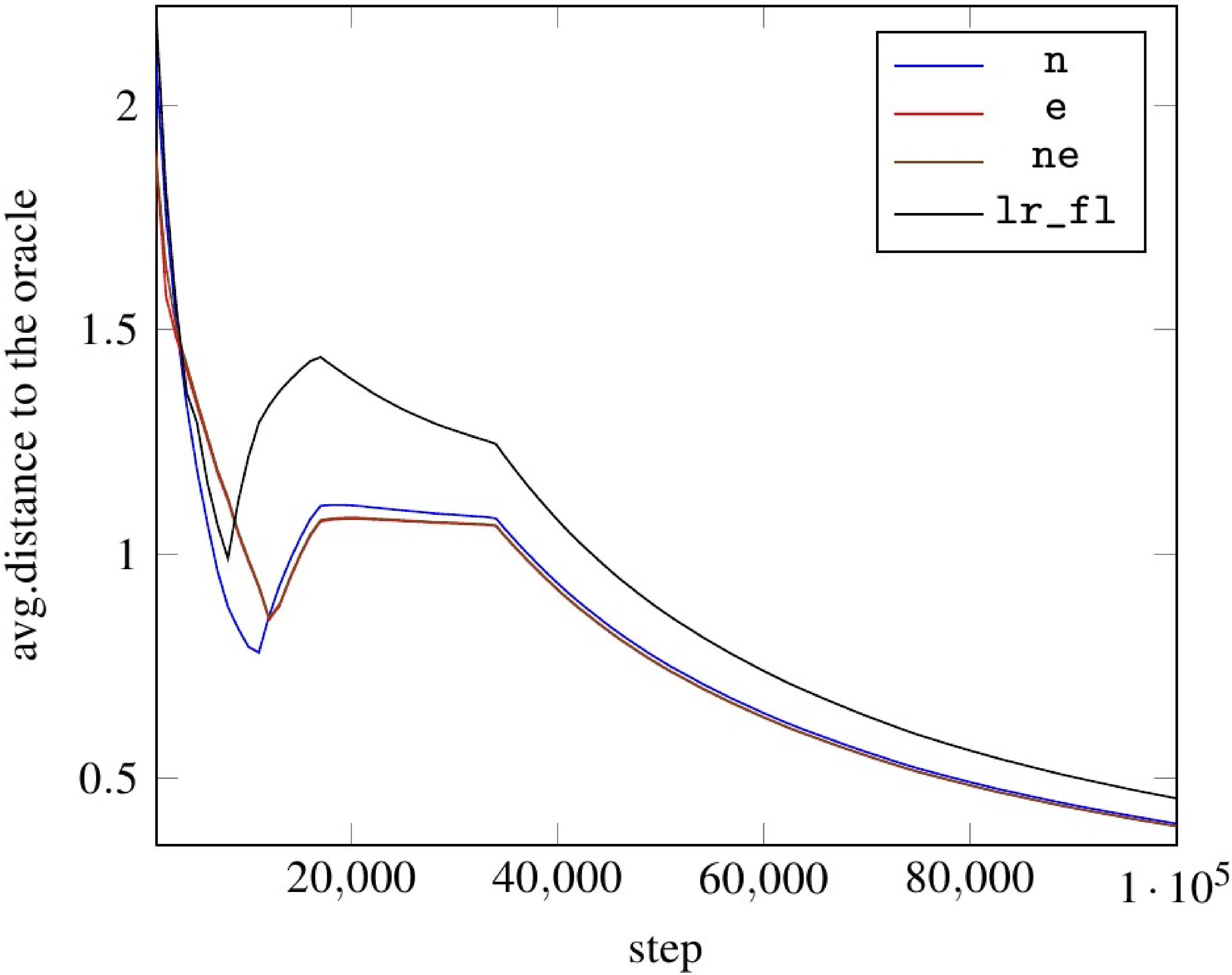
The precision

Same crawl sequence: the oracle

Precision: distance of the top node to the actual top node

Arithmetically averaged over a window of 1000 steps

For bretagne



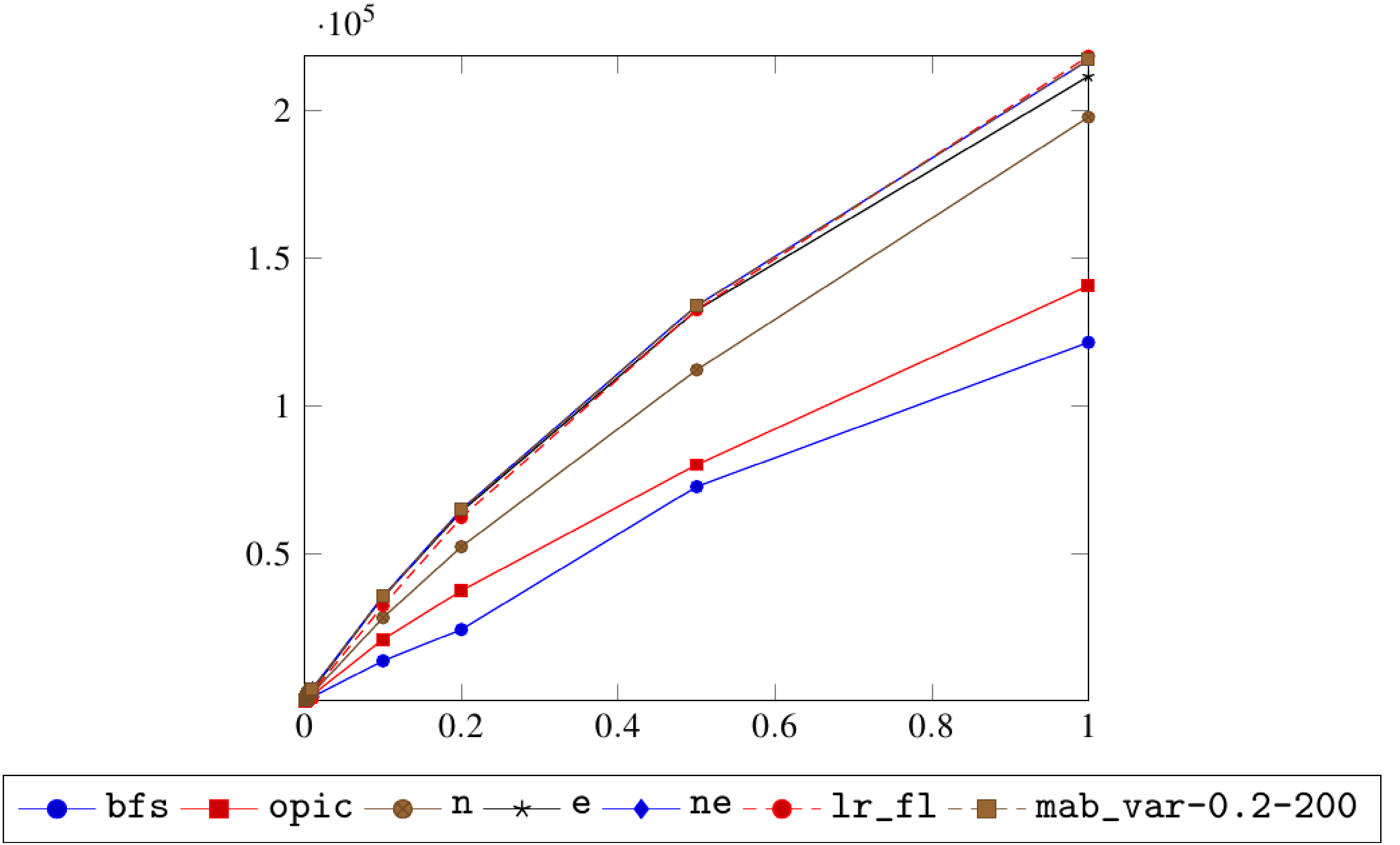
Their ability to lead crawls

Leading the crawl

Different crawl sequences:

defined by the top estimated nodes

Average graph scores for France



The multi armed-bandits

Type	100	1,000	10,000	100,000
ε	0.450	0.481	0.477	0.495
ε-`first`	0.409	0.501	0.484	0.490
`var-0.1-1000`	0.383	0.439	0.420	0.494
`var-0.2-200`	0.427	0.413	0.461	0.458

All the estimators

Estimator	100	1,000	10,000	100,000
bfs	0.147	0.132	0.130	0.207
opic	0.283	0.184	0.205	0.287
n	0.358	0.280	0.362	0.467
e	0.594	0.560	0.457	0.377
ne	0.583	0.570	0.466	0.378
lr_fl	0.325	0.382	0.466	0.504
mab_var-0.2-200	0.427	0.413	0.461	0.458

Conclusion

What we learnt

Generic model

NP-hardness offline

Refresh rate of 1

Greedy

Neighborhood features

Linear regressions

Multi-armed bandit strategy

Future work

Approximation of the optimal score

Distributed crawl

Recrawling nodes

Further multi-armed bandits comparisons

Thank you.

Finding the optimal crawl sequences in a known graph

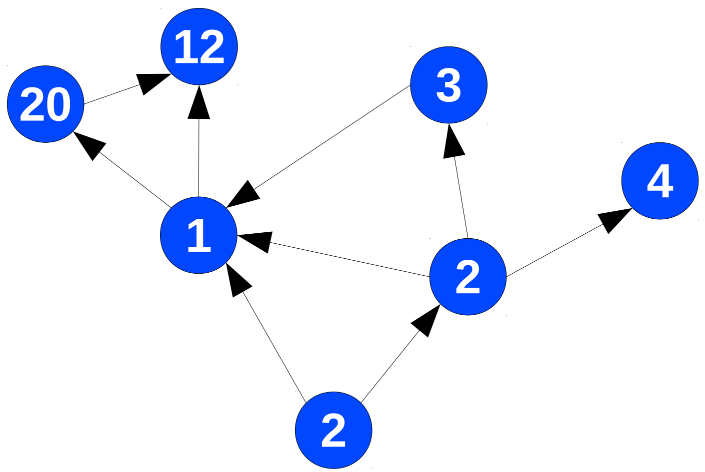
PTime many-one reduction from the LST-Graph problem

Rich friends will make you richer

The greedy strategy

Node picked = argmax(β(v)), v in frontier

Is not always optimal



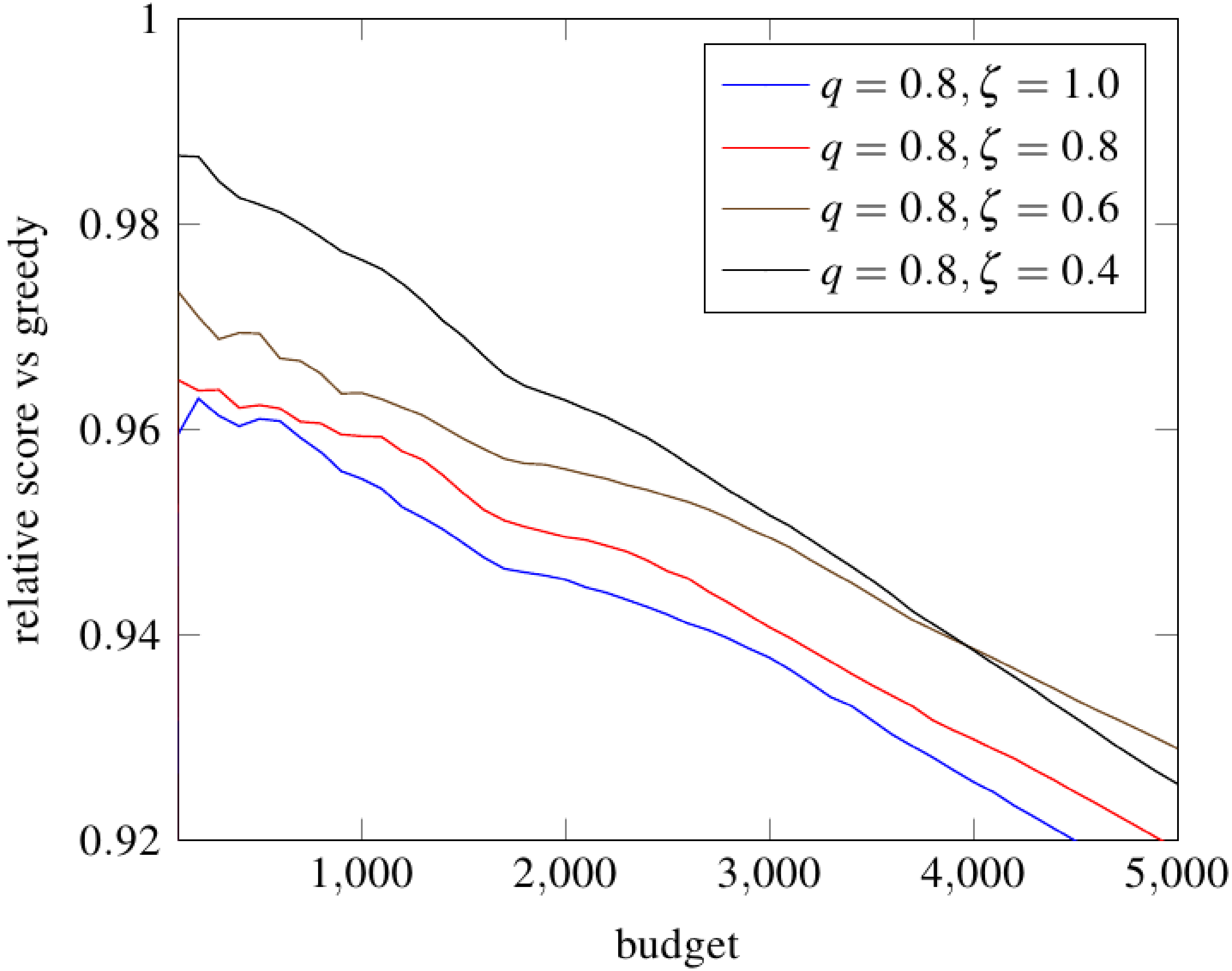
The altered greedy strategy

Node picked =

probability q: argmax(β(v))

probability 1-q: random v so that,
$\max(\beta(u)) - \beta(v) \le \zeta \times \max(\beta(u))$

Altered greedy vs greedy for jazz



The refresh rate disadvantage

When estimation takes too long

input : seed subgraph G_0, budget n

output : crawl sequence V with a score as high as possible

```
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G' ← G0;
budgetLeft ← n;
while budgetLeft > 0 do
    frontier ← extractFrontier(G');
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    estimator.scoreFrontier(G', frontier);
    r ← getRefreshRate();
    NodeSequence ←
    strategy.getNextNodes(scoredFrontier, r);
    V ← (V, NodeSequence);
    for u in NodeSequence do
        G' ← G' ∪ crawlNode(u);
    budgetLeft = budgetLeft − r
return V
```

The score degradation (%) at different steps

Refresh rate	100	1,000	10,000	100,000
2	0.4	2.2	3.9	6.4
8	1.3	6.5	12.8	18.3
32	6.6	6.5	17.5	24.3
128	38.8	10.7	19.9	29.5
1024	38.8	74.3	25.8	35.9