

Large-Scale Density-Friendly Decomposition via Convex Programming [1]

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LP formulation for Densest Subgraph

$$\begin{aligned} \text{LP}(G) \quad & \max \sum_{e \in E} w_e x_e \\ \text{s.t.} \quad & x_e \leq y_u, \quad \forall u \in e \\ & \sum_{u \in V} y_u = 1, \\ & x_e, y_u \geq 0, \quad \forall u \in V, e \in E \end{aligned}$$

Dual of the LP

DP(G)

min ρ

s.t. $\rho \geq \sum_{e: u \in e} \alpha_u^e, \quad \forall u \in V$

$\sum_{u \in e} \alpha_u^e \geq 1, \quad \forall e \in E$

$\alpha_u^e \geq 0, \quad \forall u \in e \in E$

Convex Program $\text{CP}(G)$

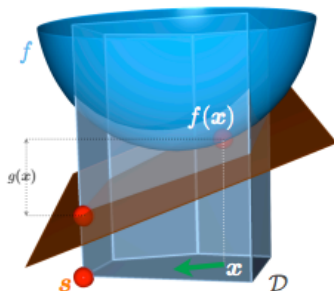
Let $Q_G(\alpha) := \sum_{u \in V} r(u)^2$, where (r, α) is an invariant pair, i.e., $r(u) = \sum_{e \in E: u \in e} \alpha_u^e$ and $\alpha_u^e + \alpha_v^e = 1$ for every $e = uv \in E$.

The convex program $\text{CP}(G)$ is defined as follows:

$$\text{CP}(G) := \min\{Q_G(\alpha) : \alpha \text{ is feasible for } \text{DP}(G)\}.$$

The Frank-Wolfe Algorithm [2]

- 1: **Input:** function f convex and continuously differentiable, a compact convex set \mathcal{D} , integer T
- 2: Let $x^{(0)} \in \mathcal{D}$
- 3: **for** $t = 1, \dots, T$ **do**
- 4: $\gamma_t \leftarrow \frac{2}{t+2}$
- 5: Compute $s := \arg \min_{s \in \mathcal{D}} \langle s, \nabla f(x^{(k)}) \rangle$
- 6: Update $x^{(k+1)} = (1 - \gamma)x^{(k)} + \gamma s$



Frank-Wolfe-Based Algorithm for Densest Subgraph

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1: for each  $e = uv$  in  $E$  in parallel do
2:    $\alpha_u^{e(0)}, \alpha_v^{e(0)} \leftarrow \frac{1}{2}$ 
3: for each  $u \in V$  in parallel do
4:    $r^{(0)}(u) \leftarrow \sum_{e \in E: u \in e} \alpha_u^{e(0)}$ 
5: for each iteration  $t = 1, \dots, T$  do
6:    $\gamma_t \leftarrow \frac{2}{t+2}$ 
7:   for each  $e$  in  $E$  in parallel do
8:      $x \leftarrow \arg \min_{v \in e} r^{(t-1)}(v)$ 
9:     for each  $u \in e$  do
10:       $\hat{\alpha}_u^e \leftarrow 1$ , if  $u = x$  and 0 otherwise.
11:    $\alpha^{(t)} \leftarrow (1 - \gamma_t) \cdot \alpha^{(t-1)} + \gamma_t \cdot \hat{\alpha}$ 
12:   for each  $u \in V$  in parallel do
13:      $r^{(t)}(u) \leftarrow \sum_{e \in E: u \in e} \alpha_u^{e(t)}$ 
14: return  $(\alpha^{(t)}, r^{(t)})$ 
```

Convergence

Theorem 1

(Convergence of the Frank-Wolfe-based Algorithm.) Let $G = (V, E)$ be an undirected graph with maximum degree Δ . Let (r^, α^*) be an invariant pair for G where α^* is an optimal solution for $\text{CP}(G)$. In Algorithm 2, for any $\epsilon > 0$ for any $t > \frac{4\Delta|E|}{\epsilon^2}$, we have $\|r^{(t)} - r^*\|_2 \leq \epsilon$.*

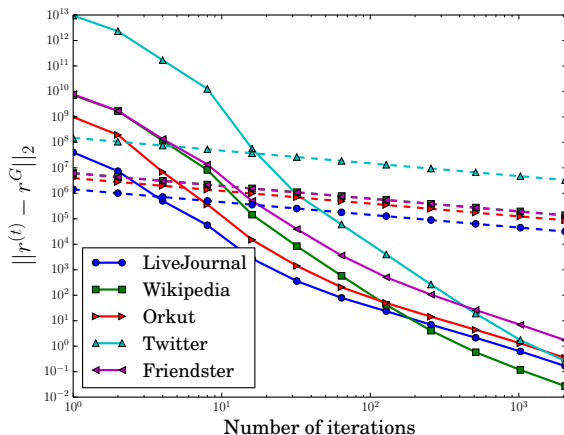
Experiments: Settings

networks	n	m
LiveJournal	4,036,538	34,681,189
Wikipedia	2,080,370	42,336,692
Orkut	3,072,627	117,185,083
Twitter	52,579,683	1,614,106,500
Friendster	124,836,180	1,806,067,135
gsh-2015	988,490,691	25,690,705,119

Table: Our set of large graphs.

Used a linux machine with 2 processors Intel Xeon CPU E5-2660 @ 2.60 GHz with 10 cores split in 2 threads each, as well as 64G of RAM DDR4 2133 MHz. We employ 10 threads.

Convergence to the r^* vector



where r^t is the r vector at step t and $r^G = r^*$.

Densest Subgraph

How to extract the densest subgraph from a sufficiently good r^t ? Use the fact that for any graph H_1, H_2 , $|\rho(H_1) - \rho(H_2)| \geq \frac{1}{|V|^2}$.

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From Thm. 1, after some step the nodes in a densest subgraph will have max r^t score. Sort the r^t 's non-increasingly: $r(v_1)^t \geq r(v_2)^t, \dots, \geq r(v_n)^t$. Recall that $r(v_1)^t$ gives an upper bound on the max density. Let G_k be the graph induced by v_1, \dots, v_k . As soon as we find a graph G_k such that $|\rho(G_k) - r(v_1)^t| < \frac{1}{n^2}$ we know that G_k is densest.

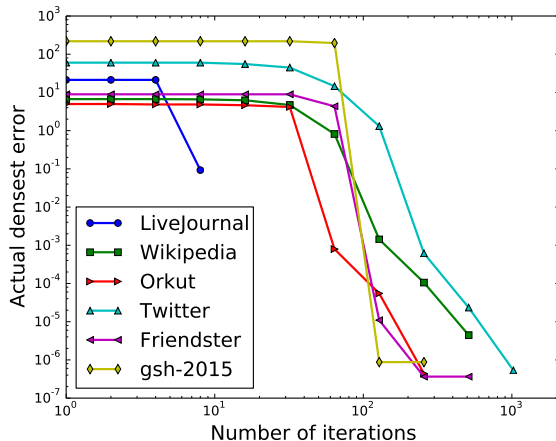
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In practice: as soon as we find a “sufficiently” small stable subset H we compute a densest subgraph in H via the LP-based algorithm or maximum flow. This works well...

Computation of the densest subgraph



where r^t is the r vector at step t and $r^G = r^*$.

K-Core and Density-Friendly Decomposition

- k -core decomposition: compute for each node v the largest integer c_v such that v is in an induced subgraph with minimum degree c_v .
- k -core decomp. might reveal the structural organization of a graph.
- It has been applied to the analysis of the internet topology [5], social network analysis [8], bioinformatics [7], analysis of the human brain [4], as well as influence analysis [3]. There is also a startup based in NYC using such an algorithm <http://www.kcore-analytics.com/>.
- In the k -core decomposition, outer cores might be denser than inner cores, which is not ideal.
- Here, we will show that the Frank-Wolfe based algorithm actually computes a so-called diminishingly-dense decomposition where inner cores are always denser than outer cores.

Quotient Graph

Definition 2 (Quotient Graph)

Given an undirected graph $G = (V, E)$, and a subset $B \subseteq V$, the quotient graph of G with respect to B is a weighted graph $G \setminus B = (\hat{V}, \hat{E}, \hat{w})$, which is defined as follows.

- $\hat{V} := V \setminus B$.
- $\hat{E} := \{e \cap \hat{V} : e \in E, e \cap \hat{V} \neq \emptyset\}$, i.e., every edge $e \in E$ not contained in B contributes towards \hat{E} .
- For $e' \in \hat{E}$, $\hat{w}(e') := |\{e \in E : e' = e \cap \hat{V}\}|$.

Diminishingly-dense Decomposition

Definition 3 (Diminishingly-dense Decomposition)

Given an undirected graph $G = (V, E, w)$, we define the diminishingly-dense decomposition \mathcal{B} of G as the sequence $\emptyset = B_0 \subsetneq B_1 \subsetneq B_2 \subsetneq \cdots \subsetneq B_k = V$ as follows:

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Initially, we set $B_0 := \emptyset$ and $G_0 := G$. For $i \geq 1$, if $B_{i-1} = V$, the decomposition is fully defined.

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Otherwise, let $G_i := G_{i-1} \setminus B_{i-1} = (V_i, E_i, w_i)$ be the quotient graph of G_{i-1} with respect to B_{i-1} . Let S_i be the maximal densest subset in G_i (with respect to w_i). We define $B_i := B_{i-1} \cup S_i$. For each $i = 1, \dots, k$, we denote $r_i = \rho_i(S_i)$. Moreover, we define the *maximal density* vector $r^G \in \mathbb{R}^V$ such that if $u \in S_i$, then $r^G(u) := r_i$.

Properties of the Decomposition

Lemma 4 (the decomposition is unique)

Given a graph G , there is a unique diminishingly-dense decomposition.

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Lemma 5 (Diminishing r_i 's)

In the diminishingly-dense decomposition in Definition 3, if $B_i \subsetneq V$, then

$$r_i > r_{i+1} \quad i = 1, \dots, k-1.$$

Lemma 6 (Diminishing Densities)

In the diminishingly-dense decomposition in Definition 3, if $B_i \subsetneq V$, then

$$\rho(B_i) > \rho(B_{i+1}) \quad i = 1, \dots, k-1.$$

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