

Fast Approximation of Betweenness Centrality through Sampling¹

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Accepted as full paper at ACM WSDM'14. Full version: <http://cs.brown.edu/~matteo/papers/RiondatoKornarop-BetweennessSampling.pdf>. This work is supported in part by the National Science Foundation under award IIS-1247581.

I. Background

Graph $G = (V, E)$, $|V| = n$, $|E| = m$

Path p from u to v : $p = (u, a_1, a_2, \dots, a_\ell, v)$

$\text{Int}(p)$ Internal nodes

For $(u, v) \in V \times V$ let \mathcal{S}_{uv} = all shortest paths from u to v

Let $\mathbb{S}_G = \bigcup_{(u,v) \in V \times V} \mathcal{S}_{uv}$ = all shortest paths in G

Betweenness of $w \in V$:

$$b(w) = \frac{1}{n(n-1)} \sum_{p_{uv} \in \mathbb{S}_G} \frac{\mathbb{1}_{\text{Int}(p)}(w)}{|\mathcal{S}_{uv}|}$$

It is the **fraction of shortest paths** that w is **internal to**
Measures **centrality** (i.e., importance) of nodes

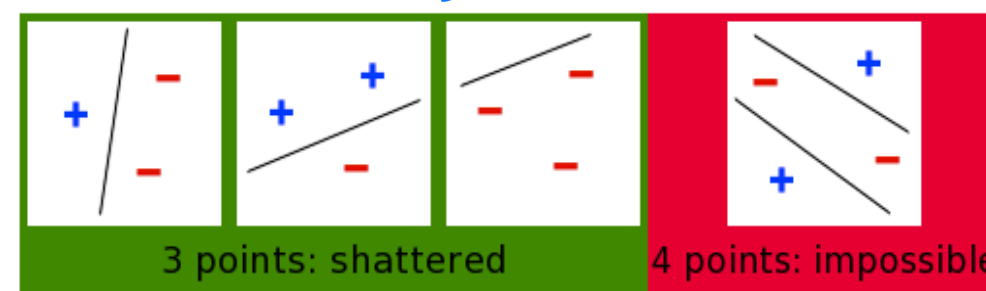
Exact algorithms exist for computing betweenness of all vertices [Brandes01]. Too **slow** for huge graphs:
 $O(n^2 \log n)$ unweighted graphs, $O(nm + n^2 \log n)$ weighted graphs

IV. VC-Dimension

Definition: Given a set of points P and a family $F \subseteq 2^P$ the **VC-Dimension** of (P, F) is the **cardinality of the largest** $A \subseteq P$ such that $\{r \cap A : r \in F\} = 2^A$

Example

$P = \mathbb{R}^2$, F = oriented halfspaces
VC-Dimension of $(P, F) = 3$



Theorem (Bound to sample size)

Let (P, F) have VC-dimension $\leq d$, and let π be a probability distribution on P . Given $\varepsilon, \delta \in (0, 1)$ let S be a collection of points from P sampled according to π with size

$$|S| \geq \frac{1}{\varepsilon^2} \left(d + \log \frac{1}{\delta} \right)$$

If d does not depend on $|P|$, then $|S|$ is also independent from $|P|$!

Then

$$\Pr \left(f \in F \text{ s.t. } \left| \mathbb{E}_\pi[f] - \frac{\sum_{c \in S} \mathbb{1}_f(c)}{|S|} \right| > \varepsilon \right) < \delta$$

i.e., the **empirical averages** for all $f \in F$ are **close to their expectations**

A sample S for which the above event is verified is called an **ε -sample for (P, F)**

II. Goals and results

Key observation: In graph mining, **fast and approximate** algorithms are often preferred over **slow but exact**

Our goal: **Speed up** by computing **fast high-quality approximation** of the betweenness of all vertices **using random sampling** (sample: collection of shortest paths)

Constraints / Desiderata:

- number of samples **must not depend on** $|V|$
- **probabilistic guarantees on quality** of approximation

Results: We developed an algorithm which computes estimations $\tilde{b}(v)$ for the betweenness $b(v)$ of all nodes. We have that, for fixed $\varepsilon, \delta \in (0, 1)$

$$\Pr(v \in V \text{ s.t. } |\tilde{b}(v) - b(v)| > \varepsilon) < \delta$$

i.e., all estimations are very accurate with high probability

V. The vertex-diameter of the graph

For $u \in V$, let $T_u = \{p \in \mathbb{S}_G : u \in \text{Int}(p)\}$

In our case: $P = \mathbb{S}_G$, $F = \{T_u, u \in V\}$

If $S = \{p_1, \dots, p_r\}$ (sampled paths) is ε -sample for (\mathbb{S}_G, F) then

$$\left| \underbrace{\mathbb{E}_\pi[T_u]}_{b(u)} - \underbrace{\frac{\sum_{p \in S} \mathbb{1}_{T_u}(p)}{|S|}}_{\tilde{b}(u)} \right| \leq \varepsilon \quad \forall u \in V$$

since $\mathbb{1}_{T_u}(p) = \mathbb{1}_{\text{Int}(p)}(u)$

We only need a bound to VC-dimension of (\mathbb{S}_G, F) !

Definition: The **vertex-diameter** of G is $\text{vd}_G = \max_{p \in \mathbb{S}_G} |\text{Int}(p)|$

An approximation of vd_G can be computed efficiently.
 vd_G is **small & shrinks** in social networks as size grows!

Thm: VC-dimension of (\mathbb{S}_G, F) is at most $\lfloor \log_2 \text{vd}_G \rfloor - 1$

Theorem: We need to sample r shortest paths with

$$r = \frac{1}{\varepsilon^2} \left(\lfloor \log_2 \text{vd}_G \rfloor - 1 + \ln \frac{1}{\delta} \right)$$

The **sample size** is independent from $|V|$

III. Our algorithm

- 1) $\forall u \in V$, let $\tilde{b}(u) = 0$
- 2) For $i = 1, \dots, r$ \leftarrow Sample Size
- 3) Sample random pair (u, v) of different nodes
- 4) Sample random shortest path p_i from \mathcal{S}_{uv}
- 5) For $w \in \text{Int}(p_i)$, $\tilde{b}(w) = \tilde{b}(w) + 1/r$
- 6) Return $\{\tilde{b}(u), u \in V\}$

Path p_{uv} is sampled with probability $\pi_{p_{uv}} = \frac{1}{n(n-1)|\mathcal{S}_{uv}|}$

Sampling a shortest path is easy: perform Dijkstra from u to v , then **backtrack** choosing predecessor z at random with probability proportional to the number of shortest paths in \mathcal{S}_{uv} that z is internal to

Choice of sample size r is **crucial for correctness**
We use **VC-dimension**, a core notion from **Statistical Learning Theory** to compute it

VI. Results of experimental evaluation

We used graphs from SNAP (<http://snap.stanford.edu>)

Very accurate estimation: $|\tilde{b}(u) - b| \ll \varepsilon, \forall u \in V$

Very fast execution, even for small ε

Better scalability than existing solution [BrandesP08]

