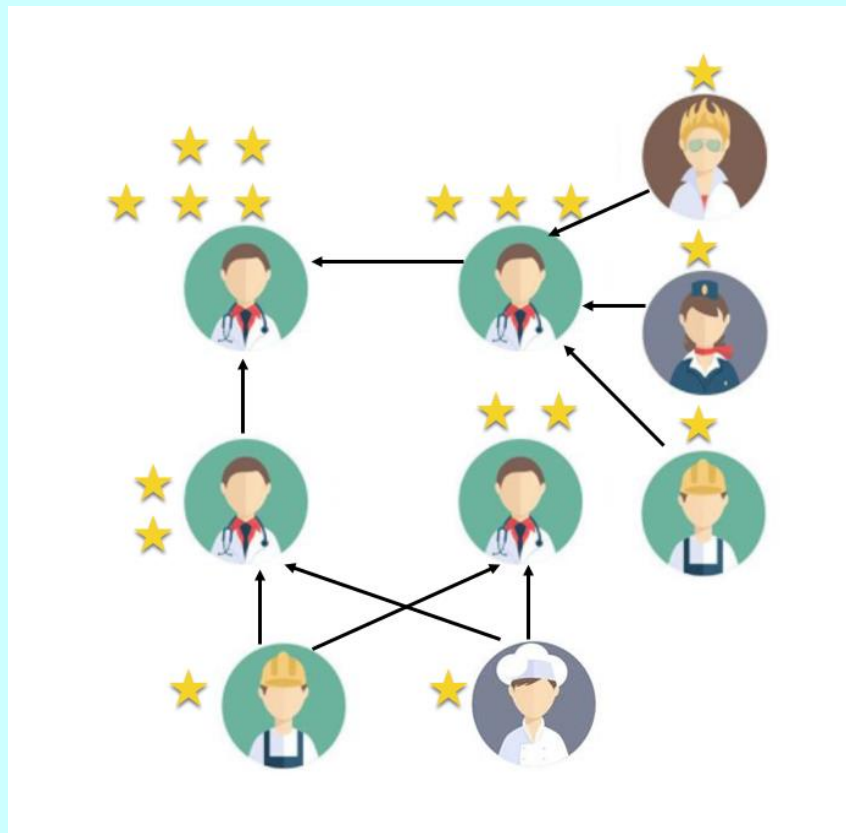


PageRank

软件学院《数据结构》讲义
内部使用



引例：社交网络中的影响力分析



Paper

The Anatomy of a Large-Scale Hypertextual Web Search Engine

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Sergey Brin received his B.S. degree in mathematics and computer science from the University of Maryland at College Park in 1993. Currently, he is a Ph.D. candidate in computer science at Stanford University where he received his M.S. in 1995. He is a recipient of a National Science Foundation Graduate Fellowship. His research interests include search engines, information extraction from unstructured sources, and data mining of large text collections and scientific data.



Lawrence Page was born in East Lansing, Michigan, and received a B.S.E. in Computer Engineering at the University of Michigan Ann Arbor in 1995. He is currently a Ph.D. candidate in Computer Science at Stanford University. Some of his research interests include the link structure of the web, human computer interaction, search engines, scalability of information access interfaces, and personal data mining.

We assume page A has pages T1...Tn which point to it (i.e., are citations). The parameter d is a damping factor which can be set between 0 and 1. We usually set d to 0.85. There are more details about d in the next section. Also C(A) is defined as the number of links going out of page A. The PageRank of a page A is given as follows:

$$PR(A) = (1-d) + d (PR(T1)/C(T1) + \dots + PR(Tn)/C(Tn))$$

Note that the PageRanks form a probability distribution over web pages, so the sum of all web pages' PageRanks will be one.

Patent

(12) United States Patent Page

(10) Patent No.: **US 7,058,628 B1**
(45) Date of Patent: ***Jun. 6, 2006**

(54) METHOD FOR NODE RANKING IN A LINKED DATABASE

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(*) Notice: Subject to any disclaimer, the term of this
patent is extended or adjusted under 35
U.S.C. 154(b) by 622 days.

This patent is subject to a terminal dis-
claimer.

(21) Appl. No.: **09/895,174**

(22) Filed: **Jul. 2, 2001**

Related U.S. Application Data

(63) Continuation of application No. 09/004,827, filed on
Jan. 9, 1998.

(60) Provisional application No. 60/035,205, filed on Jan.
10, 1997.

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(74) Attorney, Agent, or Firm—Harrity Snyder, LLP

Application US09/895,174 events ②

1997-01-10 • Priority to US3520597P

2001-07-02 • Application filed by Leland Stanford Junior
University

2006-06-06 • Application granted

2006-06-06 • Publication of US7058628B1

2019-09-23 • Adjusted expiration

Status • Expired - Lifetime

Show all events ▼

PageRank算法

$$PR(u) = \sum_{v \in D(u)} \frac{PR(v)}{|S(v)|}$$

PR(u)代表网页u的rank值

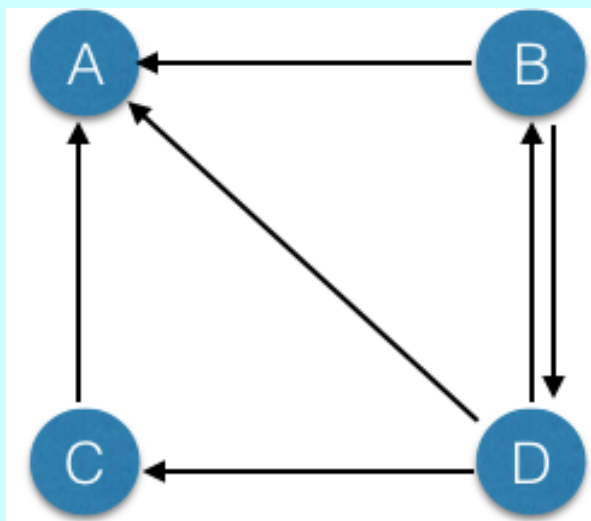
PR(v)代表网页v的rank值

D(u)代表指向u的所有网页，也就是网页图中u的入边源点集合

S(v)代表从v出发指向的网页集合，|S(v)|就是该集合的大小。

通过该公式计算，就可以得出网页集合中每一个网页的rank值。

PageRank算法



$$PR(u) = \sum_{v \in D(u)} \frac{PR(v)}{|S(v)|}$$

$$PR(A) = \frac{PR(B)}{2} + \frac{PR(C)}{1} + \frac{PR(D)}{3}$$

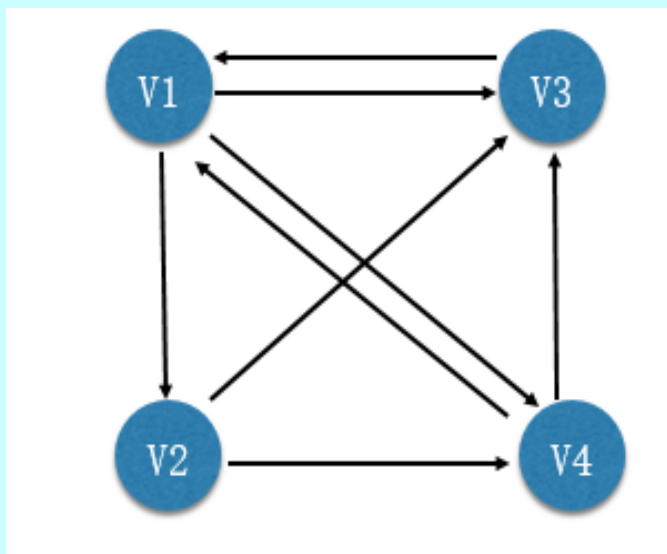
$$PR(u) = 1 - d + d * \sum_{v \in D(u)} \frac{PR(v)}{|S(v)|}$$

阻尼系数d，d表示用户到达某个页面时继续浏览的概率，那么1-d就是用户停止点击的概率

$$PR(A) = 0.15 + 0.85 * \left(\frac{PR(B)}{2} + \frac{PR(C)}{1} + \frac{PR(D)}{3} \right)$$

迭代式的PageRank计算

$$PR(u) = \sum_{v \in D(u)} \frac{PR(v)}{|S(v)|}$$



PR(v1)	PR(v2)	PR(v3)	PR(v4)
0.25	0.25	0.25	0.25

$$PR(v1) = 0.25 * 1 + 0.25 * \frac{1}{2} = 0.37$$

$$PR(v2) = 0.25 * \frac{1}{3} = 0.08$$

$$PR(v3) = 0.25 * \frac{1}{3} + 0.25 * \frac{1}{2} + 0.25 * \frac{1}{2} = 0.33$$

$$PR(v4) = 0.25 * \frac{1}{3} + 0.25 * \frac{1}{2} = 0.20$$

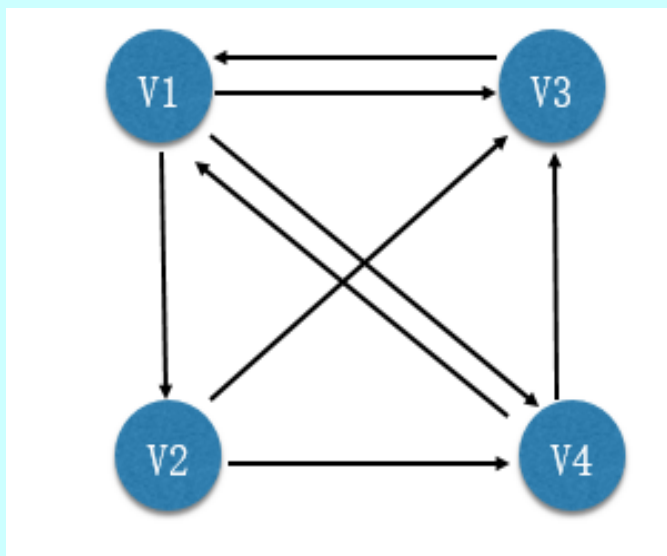
迭代式的PageRank计算

运行PageRank 4次后

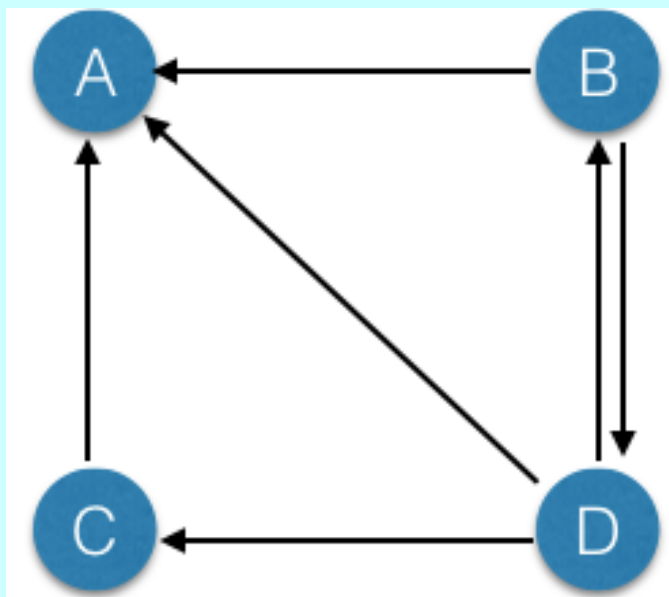
	Initial	Iter = 1	Iter = 2	Iter = 3	Iter = 4
PR(v1)	0.25	0.37	0.43	0.35	0.39
PR(v2)	0.25	0.08	0.12	0.14	0.11
PR(v3)	0.25	0.33	0.27	0.29	0.29
PR(v4)	0.25	0.20	0.16	0.20	0.19

运行PageRank 6次后

	Initial	Iter = 1	Iter = 2	Iter = 3	Iter = 4	Iter = 5	Iter = 6
PR(v1)	0.25	0.37	0.43	0.35	0.39	0.39	0.38
PR(v2)	0.25	0.08	0.12	0.14	0.11	0.13	0.13
PR(v3)	0.25	0.33	0.27	0.29	0.29	0.28	0.28
PR(v4)	0.25	0.20	0.16	0.20	0.19	0.19	0.19



基于矩阵的实现



	A	B	C	D
A	0	1	1	1
B	0	0	0	1
C	0	0	0	1
D	0	1	0	0

	A	B	C	D
A	0	1/2	1	1/3
B	0	0	0	1/3
C	0	0	0	1/3
D	0	1/2	0	0

$$PR(u) = \sum_{v \in D(u)} \frac{PR(v)}{|S(v)|}$$

```

template <typename T>
struct Row{
    int n;
    T *rdata;
    Row() {
        n = 0;
        rdata = NULL;
    }
    void set_row(int n, T *rdata) {
        assert(n > 0);
        this->n = n;
        this->rdata = rdata;
    }
    T& operator[] (int j) {
        assert(j >= 0 && j < n);
        return rdata[j];
    }
    ~Row() {
        rdata = NULL;
    }
};

```

```

template <typename T>
class Matrix{
protected:
    // m rows and n cols
    int m;
    int n;
    Row<T> *data;
public:
    Matrix() {
        m = n = 0;
        data = NULL;
    }
    Matrix(int m, int n, const T *_data = NULL) {
        initialize(m, n, _data);
    }
}

```

```

void initialize(int m, int n, const T *_data){
    // ensure parameter _m and _n are all valid
    assert(m > 0 && n > 0);
    this->m = m;
    this->n = n;
    T *buf;
    assert((buf = (T*)calloc(m * n, sizeof(T))) != NULL);
    if(_data){
        memcpy(buf, _data, sizeof(T) * m*n);
    }
    // allocate memory for each row in a matrix
    assert((data = new Row<T>[m]) != NULL);
    for(int i = 0; i < m; ++i){
        data[i].set_row(n, buf+i*n);
    }
}

```

```

Matrix(const Matrix<T> &other){
    if(&other == this)return;
    this->m = other.row_size();
    this->n = other.col_size();
    // empty, don't need to copy data
    if(m <= 0 || n <= 0)return;
    initialize(m, n, NULL);
    for(int i = 0; i < m; ++i){
        for(int j = 0; j < n; ++j){
            data[i][j] = other[i][j];
        }
    }
}

```

```

Row<T>& operator[] (int i) const{
    assert(i >= 0 && i < m);
    return data[i];
}

```

```

Matrix operator*(const Matrix<T> &other) {
    // precondition
    assert(n == other.row_size());
    // res is result to be returned
    int res_col = other.col_size();
    // create res to store result
    Matrix<T> res(m, res_col);
    for(int i = 0; i < m; ++i) {
        for(int j = 0; j < res_col; ++j) {
            res[i][j] = 0;
            // matrix A, B: sum of aik * bkj, k from 1 to n
            for(int k = 0; k < n; ++k) {
                res[i][j] += data[i][k] * other[k][j];
            }
        }
    }
    // overload operator=
    return res;
}

```

```
// avoid shadow copy
```

```
void operator=(const Matrix<T> &other) {  
    if(&other == this)return;  
    // this is not empty  
    if(this->m != 0) {  
        clear();  
    }  
    this->m = other.row_size();  
    this->n = other.col_size();  
    // empty, don't need to copy data  
    if(m <= 0 || n <= 0)return;  
    initialize(m, n, NULL);  
    for(int i = 0; i < m; ++i) {  
        for(int j = 0; j < n; ++j) {  
            data[i][j] = other[i][j];  
        }  
    }  
}
```

```
void operator+=(const Matrix<T> &other) {  
    // allow add itself  
    if(m != other.row_size() || n != other.col_size())return;  
    assert(m > 0 && n > 0 && data != NULL);  
    for(int i = 0; i < m; ++i) {  
        for(int j = 0; j < n; ++j) {  
            data[i][j] += other[i][j];  
        }  
    }  
}
```

```
// avoid shadow copy
```

```
void operator=(const Matrix<T> &other) {  
    if(&other == this)return;  
    // this is not empty  
    if(this->m != 0) {  
        clear();  
    }  
    this->m = other.row_size();  
    this->n = other.col_size();  
    // empty, don't need to copy data  
    if(m <= 0 || n <= 0)return;  
    initialize(m, n, NULL);  
    for(int i = 0; i < m; ++i) {  
        for(int j = 0; j < n; ++j) {  
            data[i][j] = other[i][j];  
        }  
    }  
}
```

```
void operator+=(const Matrix<T> &other) {  
    // allow add itself  
    if(m != other.row_size() || n != other.col_size())return;  
    assert(m > 0 && n > 0 && data != NULL);  
    for(int i = 0; i < m; ++i) {  
        for(int j = 0; j < n; ++j) {  
            data[i][j] += other[i][j];  
        }  
    }  
}
```

```
int main(int argc, char * argv[]) {  
    int row1 = 6; int col1 = 6;  
    Matrix<float> H(row1, col1, H_arr);  
    // H.print();  
    float R_arr[] = {0.2,  
                     0.2,  
                     0.2,  
                     0.2,  
                     0.2,  
                     0.2};  
    int row2 = 6; int col2 = 1;  
    Matrix<float> R(row2, col2, R_arr);  
    // basic way  
    for(int i = 1; i <= iters; ++i) {  
        Matrix<float> res = H * R;  
        printf("iter %d res is :\n", i);  
        res.print();  
        R = res;  
    }  
}
```

并行方法

```
// get idx range of a row or a col
std::pair<int, int> get_range(int sub_id, int partitions, int total_len){
    assert(partitions > 0 && total_len > 0);
    int each_siz = total_len / partitions;
    int start = sub_id * each_siz;
    // > total_len is impossible
    int end = (sub_id + 1) * each_siz;
    // special case is the last partition
    end = (sub_id == partitions - 1)?total_len:end;
    return std::make_pair(start, end);
}
```


并行方法

为何没有使用锁?

```
for(int i = 1; i <= iters; ++i){
    Matrix<float> res(row1, col2);
    // rows are divided into partitions, thread num is partitions
    std::vector<std::thread> threads;
    threads.clear();
    for(int i = 0; i < partitions; ++i){
        threads.emplace_back([&](int th_i){
            std::pair<int, int> l_rows = get_range(th_i, partitions, row1);
            // subl is part of H_arr with fixed row range
            int rows = l_rows.second - l_rows.first;
            Matrix<float> subl(rows, col1, H_arr+col1*l_rows.first);
            // subl * R, sub_res is rows * col2
            Matrix<float> sub_res = subl * R;
            // copy data in sub_res into corresponding row range in res
            for(int i = l_rows.first; i < l_rows.second; ++i){
                for(int j = 0; j < col2; ++j){
                    res[i][j] = sub_res[i - l_rows.first][j];
                }
            }
        }, i);
    }
}
```

lambda 表达式

lambda 表达式定义了一个匿名函数，并且可以捕获一定范围内的变量。lambda 表达式的语法形式可简单归纳如下：

[capture] (params) opt -> ret { body; };

其中 capture 是捕获列表，params 是参数表，opt 是函数选项，ret 是返回值类型，body 是函数体。

一个完整的 lambda 表达式看起来像这样：

```
auto f = [](int a) -> int { return a + 1; };  
std::cout << f(1) << std::endl; // 输出: 2
```

lambda 表达式

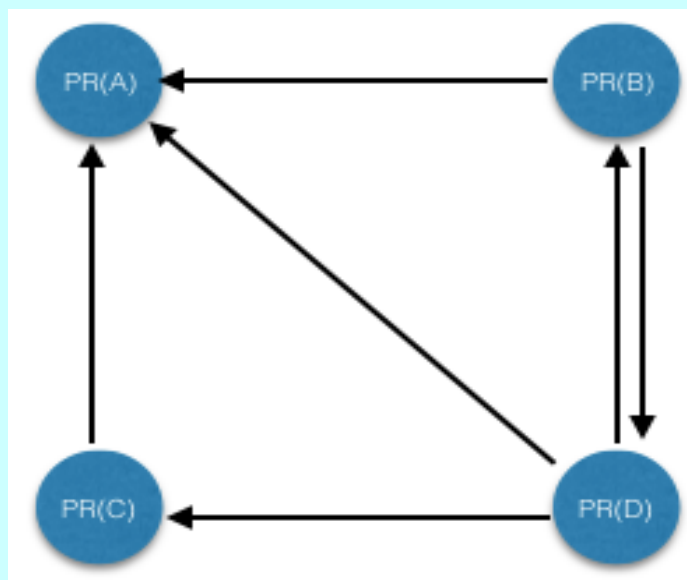
```
class CountEven
{
    int& count_;
public:
    CountEven(int& count) : count_(count) {}
    void operator()(int val)
    {
        if (!(val & 1)) // val % 2 == 0
        {
            ++ count_;
        }
    }
};

std::vector<int> v = { 1, 2, 3, 4, 5, 6 };
int even_count = 0;
for_each(v.begin(), v.end(), CountEven(even_count));
std::cout << "The number of even is " << even_count << std::endl;
```

lambda 表达式

```
std::vector<int> v = { 1, 2, 3, 4, 5, 6 };  
int even_count = 0;  
for_each( v.begin(), v.end(), [&even_count](int val)  
{  
    if (!(val & 1)) // val % 2 == 0  
    {  
        ++ even_count;  
    }  
});  
std::cout << "The number of even is " << even_count << std::endl;
```

基于图结构的实现

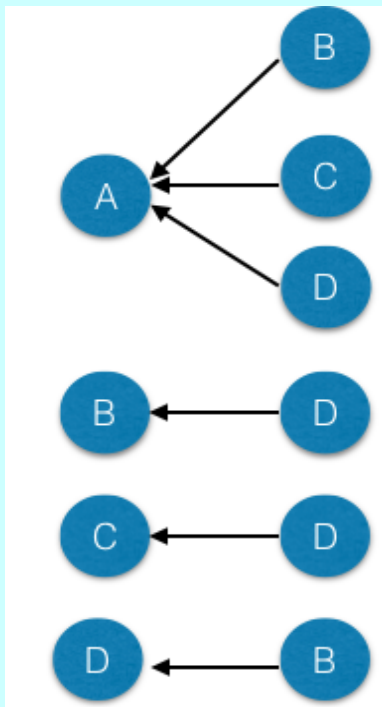
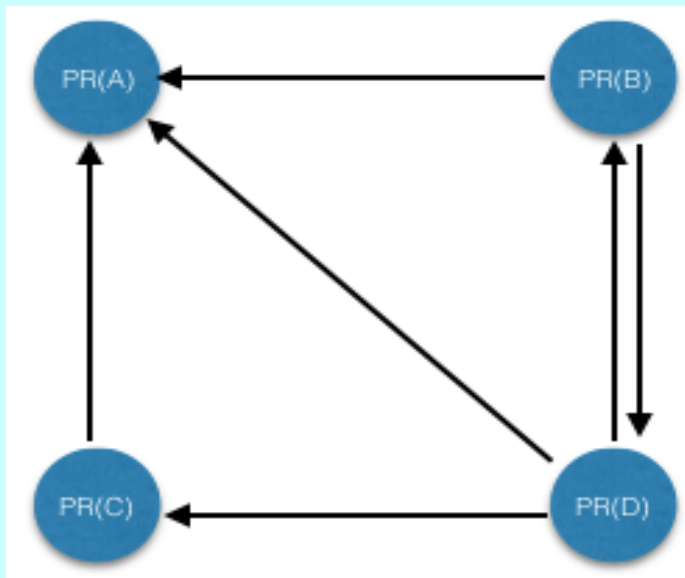


$G=(V, E, D)$ 模型

```
procedure PR_F(u, v)
    v.rank += u.rank / out_deg(u)
procedure VertexMap(u)
    u = 1-d + d*u.rank
procedure PageRank(G = (V, E, D))
    while i < iters
        for each v in V
            for each ngh u that satisfies (u, v) in E
                PR_F(u, v)
            VertexMap(v)
        i+=1
```

基于图结构的实现

CSC: compressed sparse column, 用紧凑压缩的方法来记录各个顶点的入边



源点数组



入度数组



源点范围数组



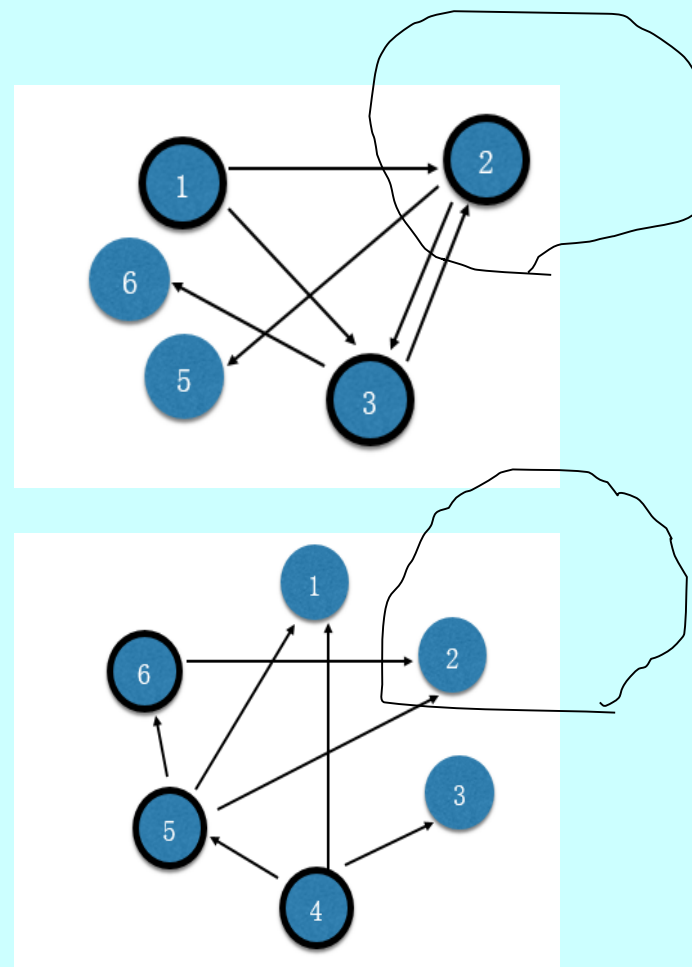
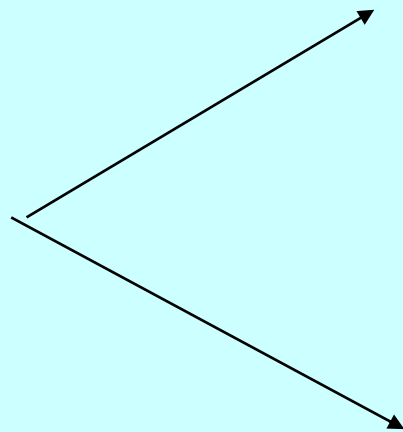
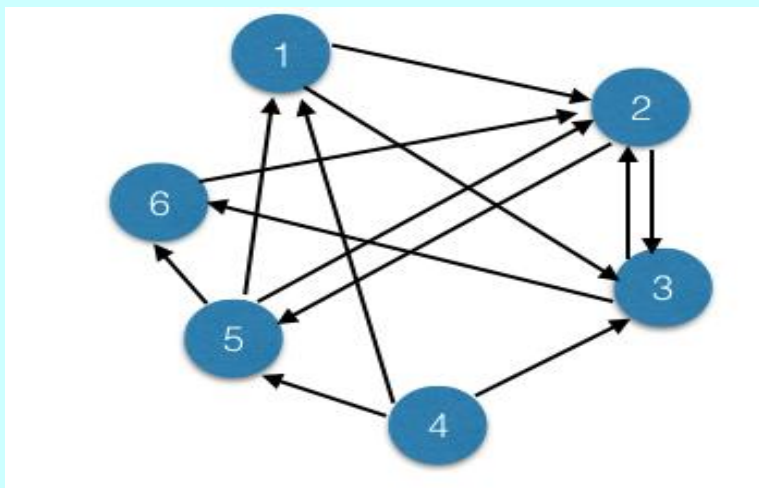
基于图结构的实现-优化

当某个顶点的rank值发生变化时，它的所有出边顶点的rank值自然需要被更新，也就是说所有活跃顶点的出边构成了活跃边集合。所以我们可以让活跃顶点主动的去更新所有邻居

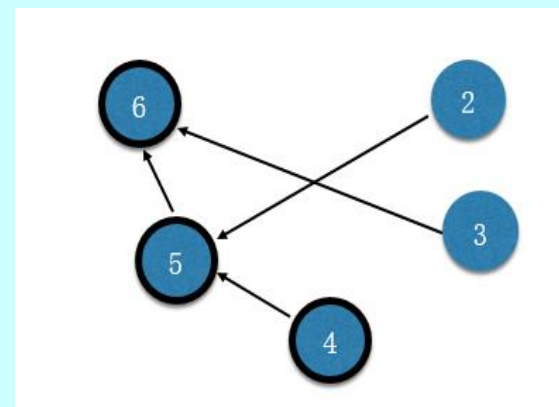
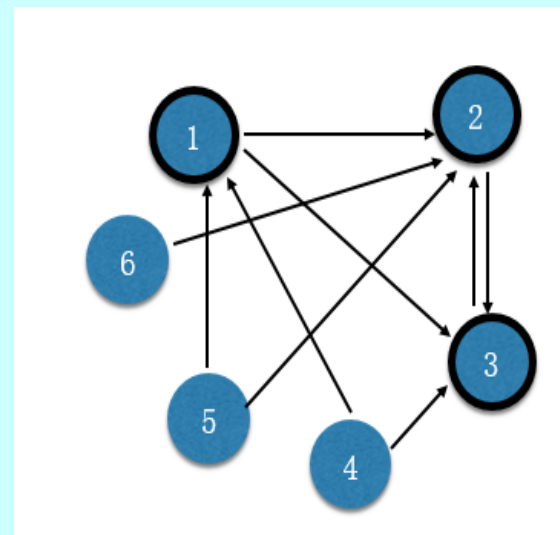
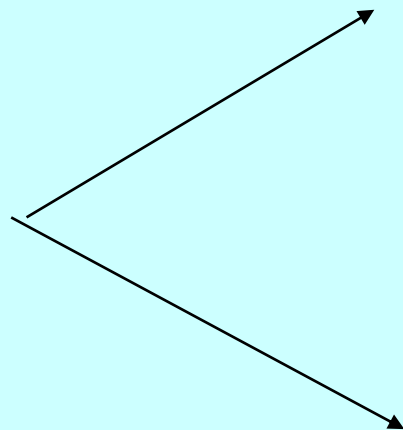
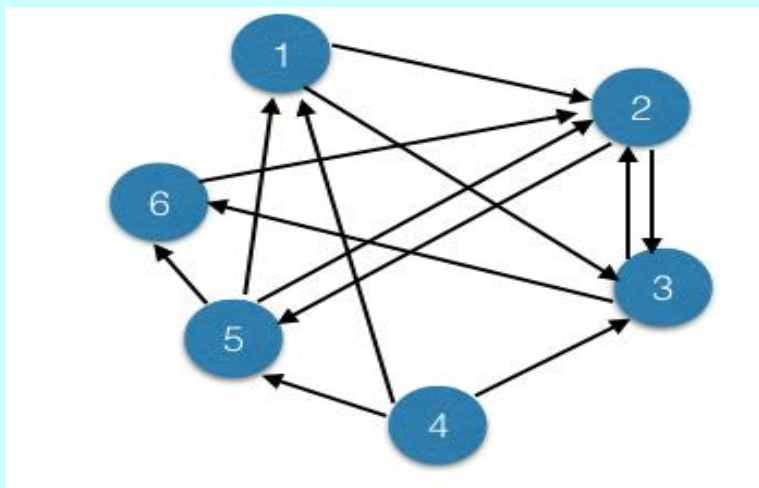
```
procedure PageRank(G = (U, E, D))  
    while i < iters  
        // push mode  
        for each active vertex u in U  
            for each ngh v that satisfies (u, v) in E  
                PR_F(u, v)  
                VertexMap(v)  
        i+=1
```

- push模型更适合活跃顶点较少的情况
- 在多线程情况下，push模式可能会同时对某个顶点进行更新（同步开销）

并行方法



并行方法-改进



Next

- 众数
- 数据结构（C++语言版）第三版 Chapter 12.2