## 3/13 CS485 Notes (Jae-Ho Lee - JL592)

## Review:

Eigenvalues of specific graphs. Connected, regular, degree d with an odd cycle.

$$
d=\lambda_{1}>\lambda_{2}>\ldots>-d
$$

If $G$ has no odd cycle, then $\lambda_{n}=-\mathrm{d}$

## Lemma

If $G$ has exactly $k$ components then

$$
\mathrm{d}=\lambda_{1}=\lambda_{2}=\ldots=\lambda_{\mathrm{k}}>\lambda_{\mathrm{k}+1} \ldots \lambda_{\mathrm{n}}=-\mathrm{d}
$$

## Proof

Adjacency matrix is block diagonal with exactly k blocks.
Eigenvalues of big matrix are union of eigenvalues of blocks

$$
\text { If } \mathrm{B} 1 \mathrm{X}=\lambda \mathrm{X} \quad\left(\begin{array}{ccccc}
B 1 & 0 & 0 & \cdots & 0 \\
0 & B 2 & & & \\
0 & & & & \\
\vdots & & & \\
0 & & & B k
\end{array}\right)\left(\begin{array}{c}
x \\
0 \\
\vdots \\
0 \\
0 \\
\vdots \\
0
\end{array}\right)=\left(\begin{array}{c}
x 1 \\
0 \\
0 \\
\vdots \\
0
\end{array}\right)
$$

D appears exactly k times as eigenvalues
All others less than d. (Proof only holds for regular d degree graph)

Corollary : A regular degree d graph is connected iff $\lambda_{1}>\lambda_{2}$

Relax regular degree d condicion, connectivity, etc
Arbitrary graphs.
Adding edges to a graph does not decrease max eigenvalue.

## Lemma

The eigenvector associated with $\lambda_{1}$ has all non-negative components.

## Proof

Let $A_{1}$ be adjacency matrix of $G_{1}$ and $\lambda_{1}\left(A_{1}\right)$ be the max eigenvalue.

$$
\lambda_{1}\left(\mathrm{~A}_{1}\right)=\gamma^{\mathrm{T}} \mathrm{~A}_{1} \gamma \leq \gamma^{\mathrm{T}} \mathrm{~A}_{2} \gamma
$$

But

$$
\begin{gathered}
\lambda_{1}\left(\mathrm{~A}_{2}\right)=\max _{|\mathrm{x}|=1} \mathrm{x}^{\mathrm{T}} \mathrm{Ax} \geq \gamma^{\mathrm{T}} \mathrm{~A}_{2} \gamma \\
\\
\geq \gamma^{\mathrm{T}} \mathrm{~A}_{1} \gamma=\lambda_{1}\left(\mathrm{~A}_{1}\right) \\
\therefore \lambda_{1}\left(\mathrm{~A}_{2}\right) \geq \lambda_{1}\left(\mathrm{~A}_{1}\right)
\end{gathered}
$$

*Note
Definition

$$
\lambda_{1}=\max _{|\mathrm{x}|=1}|\mathrm{Ax}|_{2}
$$

Theorem

$$
\begin{aligned}
\lambda_{1} & =\max \mathrm{x}_{\mathrm{x}} \frac{x^{T} A x}{x^{T} x} \\
& =\max _{|\mathrm{x}=1|} \mathrm{x}^{\mathrm{T}} \mathrm{Ax}
\end{aligned}
$$

CS 485 Lecture 22 - 13 March 2006 - second half
Jeff Wong (jmw92)

## Random Walk on a Directed Graph

- In the case of a connected undirected graph, iterating the probability vector by multiplying $\mathbf{p} \rightarrow \mathbf{A D}^{-1} \mathbf{p}$, we get a steady-state probability proportional to the degree of the graph.
- For a directed graph, we can get the iterated probability by multiplying $\mathbf{p} \rightarrow \mathbf{A} \mathbf{D}_{\mathrm{R}}{ }^{-1} \mathbf{p}$, where $\mathbf{D}_{\mathrm{R}}{ }^{-1}$ is a diagonal matrix where each element is the inverse of the sum of the rows
 of $\mathbf{A}$, equivalent to the outgoing degree of each node.
- There exists a problem: what happens at dead-end nodes, like E? The probability that we were at E just "disappears," and also, multiplying by $\mathbf{D}_{\mathrm{R}}{ }^{-1}$ causes us to multiply by $1 / 0$ for a dead end.
- One solution is to add a self-loop to every node, so that there are no dead ends. But this results in a probability that saturates at dead end nodes and is dependent on where you start.
- Google came up with a solution when looking at the web as a directed graph: at each step, with probability $\varepsilon$, reset your location and go to a random node.
- This is equivalent to adding an edge from each node to each other node; at each step we take one of these new edges with probability $\varepsilon / \mathrm{n}$. But this adds $\mathrm{n}^{2}$ new edges, which becomes unwieldy.
$\circ$ A better way: add a new node, with incoming edges from every node and outgoing edges to every node. Then, from each node, go to the new node with probability $\varepsilon$; then, at the new node, go to all other nodes with uniform probability.

How long do you have to iterate this process until you get a steady state? It depends on the graph, but it turns out that for a random graph, you approach the steady state exponentially fast.

Random Algorithms are algorithms that use the outcome of random variables (e.g. coin flips)

Example: Is $n$ prime?
If $n$ is prime, then $a^{n-1}=1 \bmod n$ for all $1<a \leq n-1$
If $n$ is not prime, then $a^{n-1} \neq 1 \bmod n$ for at least half of all $1<a \leq n-1$
The algorithm: choose 100 random $a$ 's and calculate $a^{n-1} \bmod n$. If we get any results not equal to 1 , then we know that $n$ is composite. If we get all 1 's, then we know that the probability of $n$ being composite is less than $1 / 2^{100}$.
But we need 100 random numbers ( $100 \log n$ bits) to do this. We would like to reduce this number.

## Spectrum of a Star

The spectrum of a graph is the set of eigenvalues. A star has an adjacency matrix


$$
\mathbf{A}=\left(\begin{array}{ccccc}
0 & 1 & 1 & \cdots & 1 \\
1 & & & & \\
1 & & 0 & & \\
\vdots & & & & \\
1 & & & & \text { This has rank}=2 . .20
\end{array}\right.
$$

We can see the following easily:

$$
\begin{aligned}
& \left(\begin{array}{ccccc}
0 & 1 & 1 & \cdots & 1 \\
1 & & & \\
1 & 0 & & \\
\vdots & & & & \\
1 & & & & \sqrt{n-1} \\
1 \\
1 \\
\vdots \\
1
\end{array}\right)=\left(\begin{array}{c}
n-1 \\
\sqrt{n-1} \\
\sqrt{n-1} \\
\vdots \\
\sqrt{n-1}
\end{array}\right) \text { so one eigenvalue is } \sqrt{n-1} \\
& \left(\begin{array}{lllll}
0 & 1 & 1 & \cdots & 1 \\
1 & & & \\
1 & 0 & & 0 \\
\vdots & & & & \\
1 & & & & \\
\vdots \\
\vdots \\
-(n-1) \\
\vdots \\
\vdots \\
0
\end{array}\right)=\left(\begin{array}{c}
0 \\
0 \\
0 \\
\vdots \\
0
\end{array}\right) \text { so (n-2) eigenvalues are } 0 \\
& \left(\begin{array}{ccccc}
0 & 1 & 1 & \cdots & 1 \\
1 & & & & -\sqrt{n-1} \\
1 & 0 & & \\
\vdots & & & & \\
1 & & & \\
1 \\
\vdots \\
\vdots \\
1
\end{array}\right)=\left(\begin{array}{c}
n-1 \\
-\sqrt{n-1} \\
-\sqrt{n-1} \\
\vdots \\
-\sqrt{n-1}
\end{array}\right) \text { so one eigenvalue is }-\sqrt{n-1}
\end{aligned}
$$

