Why PageRank Converges?

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May 17, 2016

The PageRank equation is:

$$\vec{P}^{t+1} = \lambda \vec{A} \vec{P}^t + \mu \vec{Q} \tag{1}$$

where $0 \le \lambda, \mu \le 1, \vec{A}$ is a transition matrix with each column summing to 1 and \vec{Q} can be any vector with the same dimension of \vec{P} .

Why PageRank (1) converges?

Prove([1]):

Suppose $\vec{P}^0 = \pi$, we have $\vec{P}^n = (\lambda \vec{A})^n \pi + \sum_{k=0}^{n-1} (\lambda \vec{A})^k \mu \vec{Q}$. Since $0 \le \lambda, \mu \le 1$ and the eigenvalues of the transition matrix \vec{A} are in [-1,1], we have $\lim_{n\to\infty} (\lambda \vec{A})^n = \vec{0}$ and $\lim_{n\to\infty} \sum_{k=0}^{n-1} (\lambda \vec{A})^k = (\vec{I} - \lambda \vec{A})^{-1}$. So \vec{P}^n finally converges to $\vec{P}^* = (\vec{I} - \lambda \vec{A})^{-1} \mu \vec{Q}$. So the value of \vec{P}^* is only relavant to \vec{A} , \vec{Q} , λ and μ and the convergence is irrelevant to \vec{Q} .

References

[1] Wei Feng, Jianyong Wang. Incorporating Heterogeneous Information for Personalized Tag Recommendation in Social Tagging Systems. KDD, 2012