Network Learning

Steve Poulson

STG

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Outline

Motivation
- How to simulate the growth of power law graph
- New Link / Node prediction
- Implementation

Outline

Algorithm

Data: Directed Graph A
Result: Digraph B with n new vertices, m new edges
while *not n vertices* **do**
    pick random edge (v_1, v_2) from A where $v_1 \in$ B
    add v_2 add (v_1, v_2) to graph B
end
while *not m edges added* **do**
    pick random edge (v_1, v_2) from A where $v_1, v_2 \in$ B
    add (v_1, v_2) to graph B
end

Algorithm 1: Grow

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Supervised learning problem

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- $\min(L(f(\phi(\mathbf{A^t})), \mathbf{Y}))$

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Feature Function ϕ

Maps $\mathbf{A}_{i,j} \rightarrow (x_1 \ldots x_n)$

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- Modularity
- Cosine Distance of neighbour list
- Betweeness Centrality

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- Power Law graphs scale invariant so local features should characterize graph
- Can use Hadoop Map calculates subset of local features, reduce assembles training set which classifier runs on

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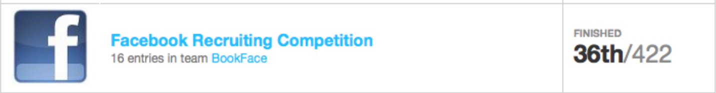
Let's try it on a Kaggle competition

- Prototyped on sklearn / networkx
- Hadoop cluster on AWS
- Java: Weka / Hadoop / cern.colt.matrix / Jung
- Random Forrest classifer beat rest

Kaggle Evaluation



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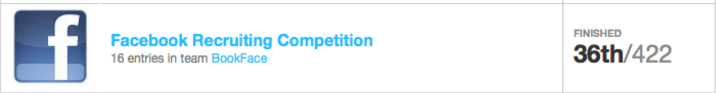

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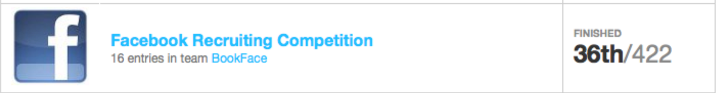

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Summary

- Power law Sampling gives a time varying dataset
- Random Forrest best
- Pretty good results