13.5 Supervised Random Walk Case Studies

DATASCI W261

Machine Learning at Scale

Case Study: Coauthorship Networks

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- Selected from four areas of physics

Results: Predicting Coauthorship

Learning Method	AUC	Prec@20
Random Walk With Restart	0.63831	3.41
Adamic-Adar	0.60570	3.13
Common Friends	0.59370	3.11
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Table 2. Hep-Ph coauthorship network. DT: decision tree, LR: logistic regression, and SRW: supervised random walks.

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Out of 20 authors recommended, over 20% (4.25) happen in the near future.

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- Evaluated on 100 test users

Results: Facebook Study

Learning Method	AUC	Prec@20
Random Walk With Restart	0.81725	6.80
Degree	0.58535	3.25
DT: Node features	0.59248	2.38
DT: Path features	0.62836	2.46
DT: All features	0.72986	5.34
LR: Node features	0.54134	1.38
LR: Path features	0.51418	0.74
LR: All features	0.81681	7.52
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Table 3. Results for the Facebook data set.

Out of 20 friendships Facebook recommends, nearly 40% are realized in the near future.

Algorithm

Extension: Global W for 100 training nodes. Test on 100 testing nodes.

- Algorithm works only for recommendation for one node or user.
  - If we want to give recommendations to multiple users, we need to run it multiple times.
- How to extend it to multiple nodes or users?
- Answer: Find best θ based on training data.

$$arg\ min_{\theta} \sum_{s \in S} \sum_{p \in P} \sum_{n \in N} \delta(r_p < r_n) + \lambda||\theta||^2$$

Penalty for violating constraint $r_p > r_n$

S are the nodes we want to give recommendation

Positive nodes

Negative nodes

r_x … score of node x on a weighted graph with edge weights $f_\theta(x, y)$

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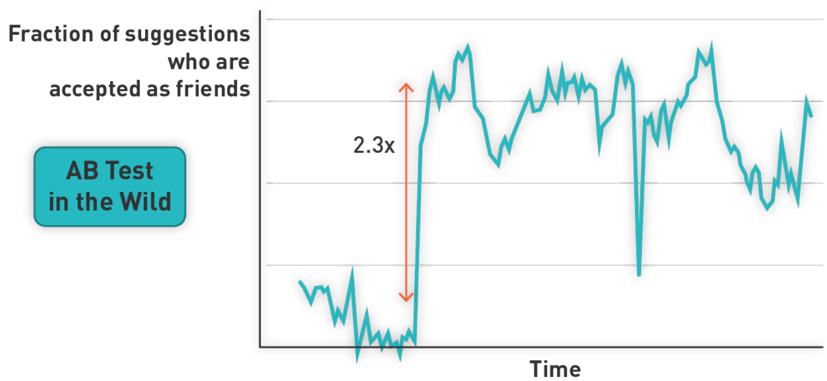

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- Fertile area for research and development