

RankMerging: a supervised learning method to predict links in social networks.

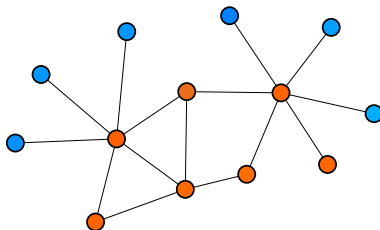
Lionel Tabourier

DyNak II
September 2014, Monday 15th

Context and problem

The phone service provider problem

Weighted network of users : $w(i,j)$ = number of calls $i-j$



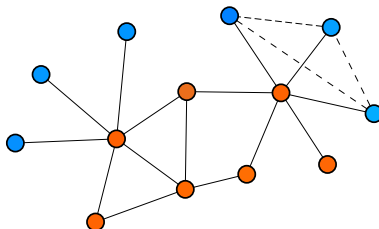
Unknown blue-blue links, yet important for commercial strategy...

How to guess these links ?

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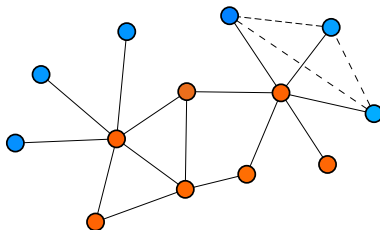
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Unknown blue-blue links, yet important for commercial strategy...

How to guess these links ?

General problem : discovering missing links

Crawled graph : (V, E) , Real graph : (V, E')

Discover links in $E' \setminus E$

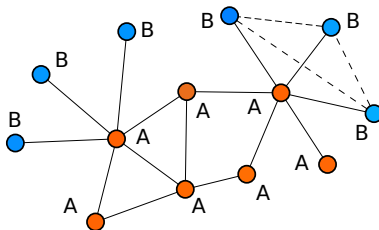
Data for supervised prediction

Dataset - Whole set (test set)

~ 1,130,000 nodes : 75% A , 25% B

~ 750,000 links

~ 50,000 B—B links to guess



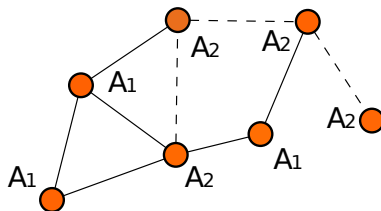
Data for supervised prediction

Dataset - Learning set

~ 850,000 nodes : $\frac{2}{3} A_1$, $\frac{1}{3} A_2$

~ 600,000 links

~ 50,000 A_2 — A_2 links to guess



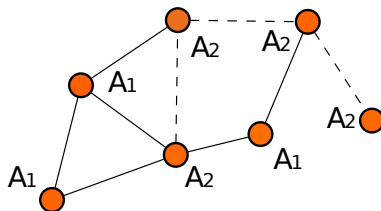
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~ 850,000 nodes : $\frac{2}{3} A_1$, $\frac{1}{3} A_2$

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Tunable number of predictions

depending on commercial strategy

General prediction method

An unbalanced classification problem

For any (unlinked) pair of nodes, is there a missed link or not ?

two classes : yes / no

unbalanced classes : much more pairs of nodes than missed links

General prediction method

An unbalanced classification problem

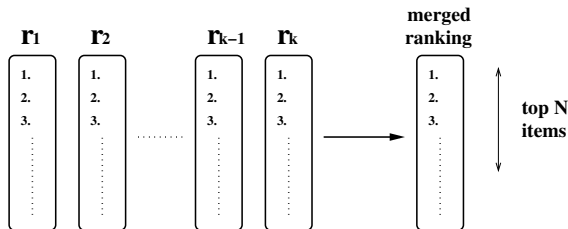
For any (unlinked) pair of nodes, is there a missed link or not ?

two classes : yes / no

unbalanced classes : much more pairs of nodes than missed links

Classification by ranking

Items (pairs) ranked according to various methods :



comes to a learning-to-rank problem

Basic unsupervised ranking methods

Structural scoring

example : common neighbors in weighted networks

$$s_{CN_w}(i, j) = \sum_{k \in \mathcal{N}(i) \cap \mathcal{N}(j)} w(i, k) \cdot w(j, k)$$

Other examples

- **local structure** : Jaccard index, Adamic-Adar index, ...
- **global structure** : Katz index, Random Walk, Hitting Time, Preferential Attachment ...

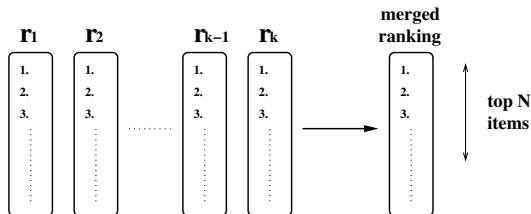
Many other : node-based, relation-based...

we only consider **structural methods**

see Al Hasan et al. (SDM06 - LACS ws)

Combining unsupervised methods

General principle



Consensus methods

see Dwork et al. (WWW'01)

- **Averaging rankings** : Borda's method
- Other methods : median (MedRank), Markov chain mixing...

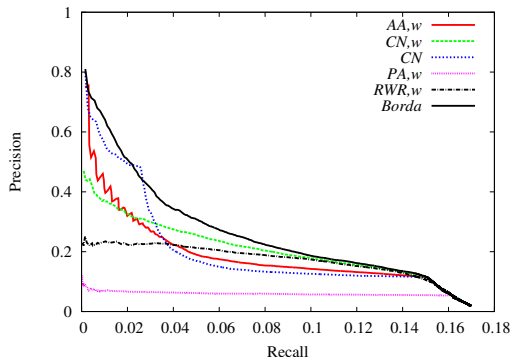
Simple to implement, (quasi-)linear complexity

Unsupervised methods : results (learning set)

Visualization metrics

Variable number of predictions, depends on strategy

Trade-off between Precision and Recall



Supervised framework

Using classic methods

see Pujari et al. (WWW'12 - MSDN ws)

Supervised methods for classification problems :
Classification Trees, Nearest Neighbor, SVM, AdaBoost...

But fixed number of predictions

Supervised framework

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Using pairwise transform

see Pedregosa et al. (MLMI 2012)

item X with ranks $\{x_1, x_2, \dots, x_k\}$

item Y with ranks $\{y_1, y_2, \dots, y_k\}$

From $\{(y_1 - x_1), (y_2 - x_2), \dots, (y_k - x_k)\}$, learn if is X over Y

Back to a classification problem

But with ranking size S : $O(S^2) \Rightarrow$ too many pairs

Aggregation with *RankMerging*

Learning process

- 1. **Define window** \mathcal{W}_i of size s : next top- s pairs of ranking i .
- 2. **Measure quality** : number of true links in the window.
- 3. **Select highest quality ranking** : its top pair is selected.
- 4. **Register** selected rankings : index ϕ_i .
- 5. **Update windows**.
- 6. **Iterate** from 2.

Testing process

Use learned ϕ_i during learning to **aggregate rankings** on test set.

Warning : a pair can only be predicted once.
+ **scaling factor** if learning set size \neq testing set size

Learning example

Two rankings r_A and r_B

Grey background : **window** (size 5)

Green background : **selected**

Red background : **forbidden**

r_A	tp	r_B	tp
(1,2)		(5,18)	x
(1,4)	x	(1,2)	
(5,6)	x	(8,9)	
(6,12)	x	(5,6)	x
(5,18)	x	(7,11)	x
(3,4)		(6,9)	x
(4,9)	x	(1,14)	
(7,11)	x	(2,9)	
(2,9)		(3,7)	

$$\phi_A = 0, \phi_B = 0$$

Learning example

Two rankings r_A and r_B

Grey background : **window** (size 5)

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r_A	tp	r_B	tp
(1,2)		(5,18)	x
(1,4)	x	(1,2)	
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(6,12)	x	(5,6)	x
(5,18)	x	(7,11)	x
(3,4)		(6,9)	x
(4,9)	x	(1,14)	
(7,11)	x	(2,9)	
(2,9)		(3,7)	

$$\phi_A = 1, \phi_B = 0$$

Learning example

Two rankings r_A and r_B

Grey background : **window** (size 5)

Green background : **selected**

Red background : **forbidden**

r_A	tp	r_B	tp
(1,2)		(5,18)	x
(1,4)	x	(4,2)	
(5,6)	x	(8,9)	
(6,12)	x	(5,6)	x
(5,18)	x	(7,11)	x
(3,4)		(6,9)	x
(4,9)	x	(1,14)	
(7,11)	x	(2,9)	
(2,9)		(3,7)	

$$\phi_A = 1, \phi_B = 1$$

Learning example

Two rankings r_A and r_B

Grey background : **window** (size 5)

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r_A	tp	r_B	tp
(1,2)		(5,18)	x
(1,4)	x	(4,2)	
(5,6)	x	(8,9)	
(6,12)	x	(5,6)	x
(5,18)	x	(7,11)	x
(3,4)		(6,9)	x
(4,9)	x	(1,14)	
(7,11)	x	(2,9)	
(2,9)		(3,7)	

$$\phi_A = 2, \phi_B = 1$$

Learning example

Two rankings r_A and r_B

Grey background : **window** (size 5)

Green background : **selected**

Red background : **forbidden**

r_A	tp	r_B	tp
(1,2)		(5,18)	x
(1,4)	x	(4,2)	
(5,6)	x	(8,9)	
(6,12)	x	(5,6)	x
(5,18)	x	(7,11)	x
(3,4)		(6,9)	x
(4,9)	x	(1,14)	
(7,11)	x	(2,9)	
(2,9)		(3,7)	

$$\phi_A = 3, \phi_B = 1$$

Test example

Link prediction on test set

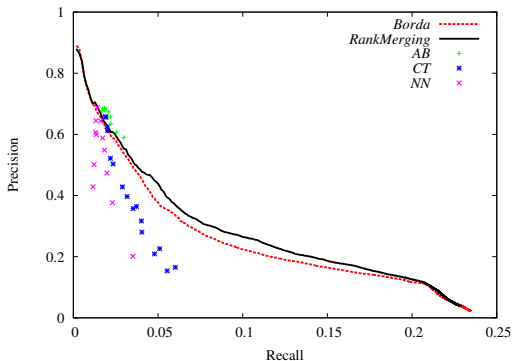
learning step s	ϕ_A	ϕ_B
1	1	0
2	1	1
3	2	1
4	3	1

r_A	r_B		r_A	r_B		r_A	r_B		r_A	r_B
(2,8)	(1,8)		(2,8)	(1,8)		(2,8)	(1,8)		(2,8)	(1,8)
(3,9)	(1,7)		(3,9)	(1,7)		(3,9)	(1,7)		(3,9)	(1,7)
(1,8)	(5,11)		(1,8)	(5,11)		(1,8)	(5,11)		(1,8)	(5,11)
(5,11)	(8,10)	→	(5,11)	(8,10)		(5,11)	(8,10)	→	(5,11)	(8,10)
(4,7)	(4,5)		(4,7)	(4,5)		(4,7)	(4,5)		(4,7)	(4,5)
(3,6)	(3,9)		(3,6)	(3,9)		(3,6)	(3,9)		(3,6)	(3,9)
(2,3)	(3,6)		(2,3)	(3,6)		(2,3)	(3,6)		(2,3)	(3,6)

Results (test set)

Aggregated rankings

*Adamic-Adar, Common Neighbors, Jaccard, Katz, Preferential Attachment, Random Walk with Restart and **Borda** (baseline)*



+8.2% area increase to baseline

Pros and Cons

Advantages

- **Addition of any ranking increases performance**
- **Scalable** : $O(N.\alpha)$, α : number of rankings , N predictions
- **Simplicity** (see lioneltabourier.fr/program.html)

Add as many ranking methods as possible to improve.

Drawbacks

- Windows size imply an **averaging effect** on prediction quality

Not suited for high precision on few items.

Conclusion

PSP : Additional information sources

duration of interactions, text messages

localization ? individual attributes (age, gender) ? usages (apps) ?

General : Relevant when...

Many complementary sources of information

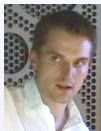
Each source yields low precision

Fields of application ?

- incomplete data sampling
- network growth microdynamic
- biomedical engineering

Other suggestions ?

Thanks for your attention !



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