
The game of go as a complex network

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Supported by EC FET Open project NADINE

CNRS and Région Midi-Pyrénées

B.G. and O. Giraud, Europhysics Letters 97 68002 (2012)

Vivek Kandiah, B.G. and O. Giraud, in preparation

NADINE project REVIEW 14 November 2013, Toulouse

Networks

- > **Nadine project**: new tools for directed network structure analysis
 - > **Important examples** from recent technological developments: World Wide Web, social networks...
 - > But network theory can be applied also to less recent objects
In particular, study of **human behavior**: languages, friendships...
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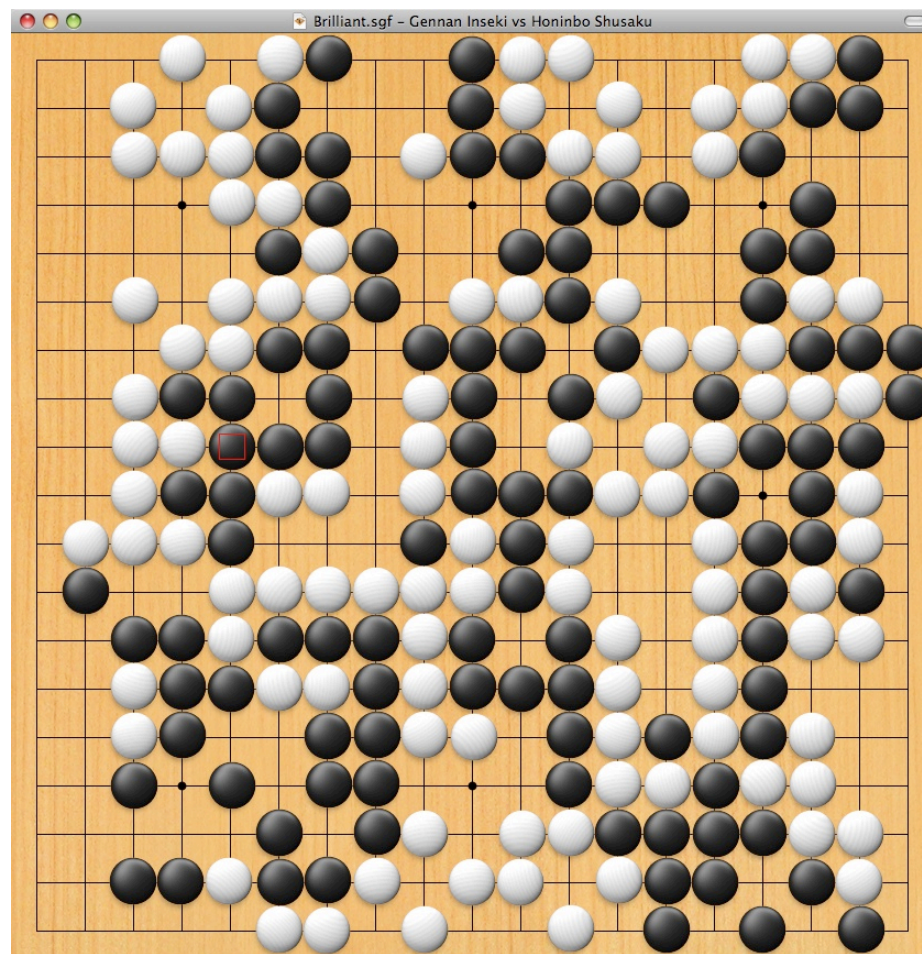
Networks for games

- >Network theory **never applied to games**
- >Games represent a **privileged approach** to human decision-making
- >Can be very difficult to **modelize or simulate**
- >While Deep Blue famously beat the world chess champion Kasparov in 1997, **no computer program has beaten a very good go player even in recent times.**



Rules of go

- > **White and black stones** alternatively put at **intersections** of 19 x19 lines
- > **Stones without liberties** are removed
- > **Handicap stones** can be placed
- > Aim of the game: construct **protected territories**
- > **total number of legal positions** 10^{171} , compared to 10^{50} for chess



Databases

->We use **databases of expert and amateur games** in order to construct networks from the different sequences of moves, and study the properties of these networks

->Databases available at <http://www.u-go.net/>

->Whole available record, from 1941 onwards, of the most important historical **professional Japanese go tournaments**:

->To increase statistics and compare with professional tournaments, **135 000 amateur games** also used.

->**Level of players** is known

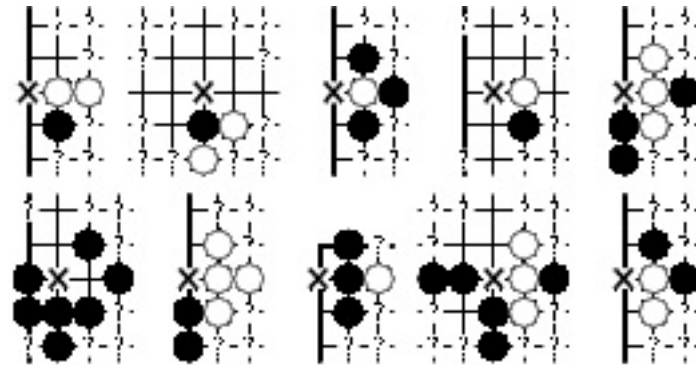
Vertices of the networks

->"plaquette" : three sizes: 1) 3x3 intersections, 2) 3x3 intersections with atari status of nearest neighbours, 3) diamond of 3 x3 +4 intersections

->We identify plaquettes related by symmetry or with color swapped

->Respectively 1107, 2051 and 193995 nonequivalent plaquettes with empty centers

->vertices of our network



Links of the network

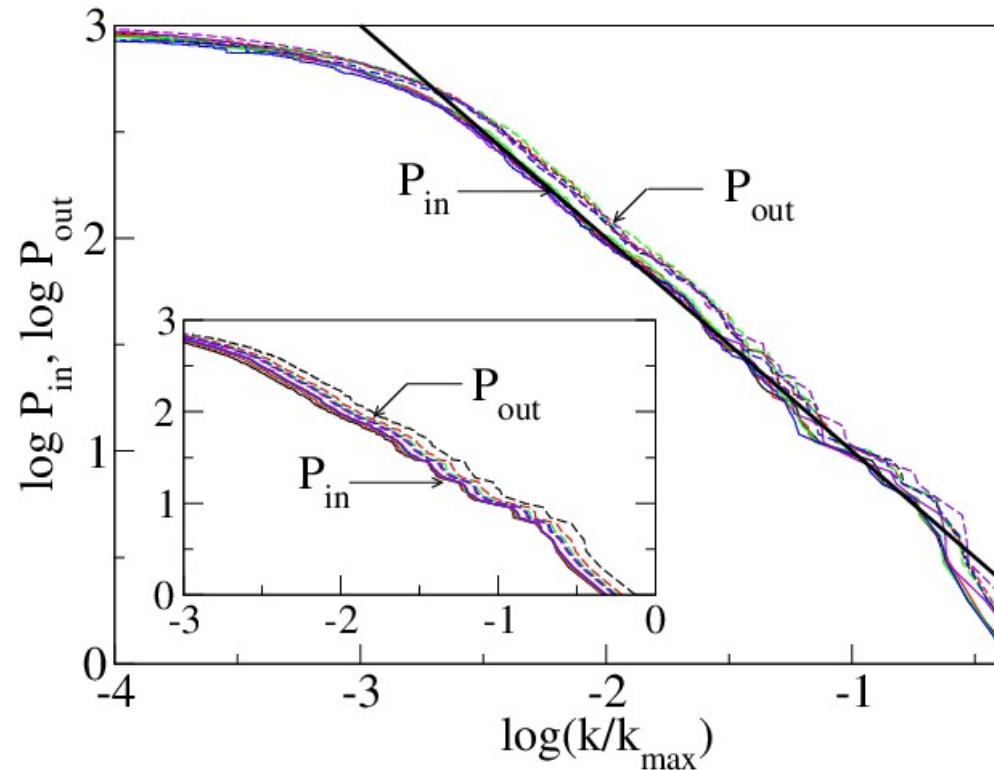
-> **we connect vertices** corresponding to moves a and b if b **follows a in a game** at a **distance $< d=5$**

-> **Sequences of moves follow Zipf's law** (cf languages)
Exponent decreases as longer sequences reflect individual strategies

-> amateur database departs from all professional ones, playing more often at shorter distances

Links distribution

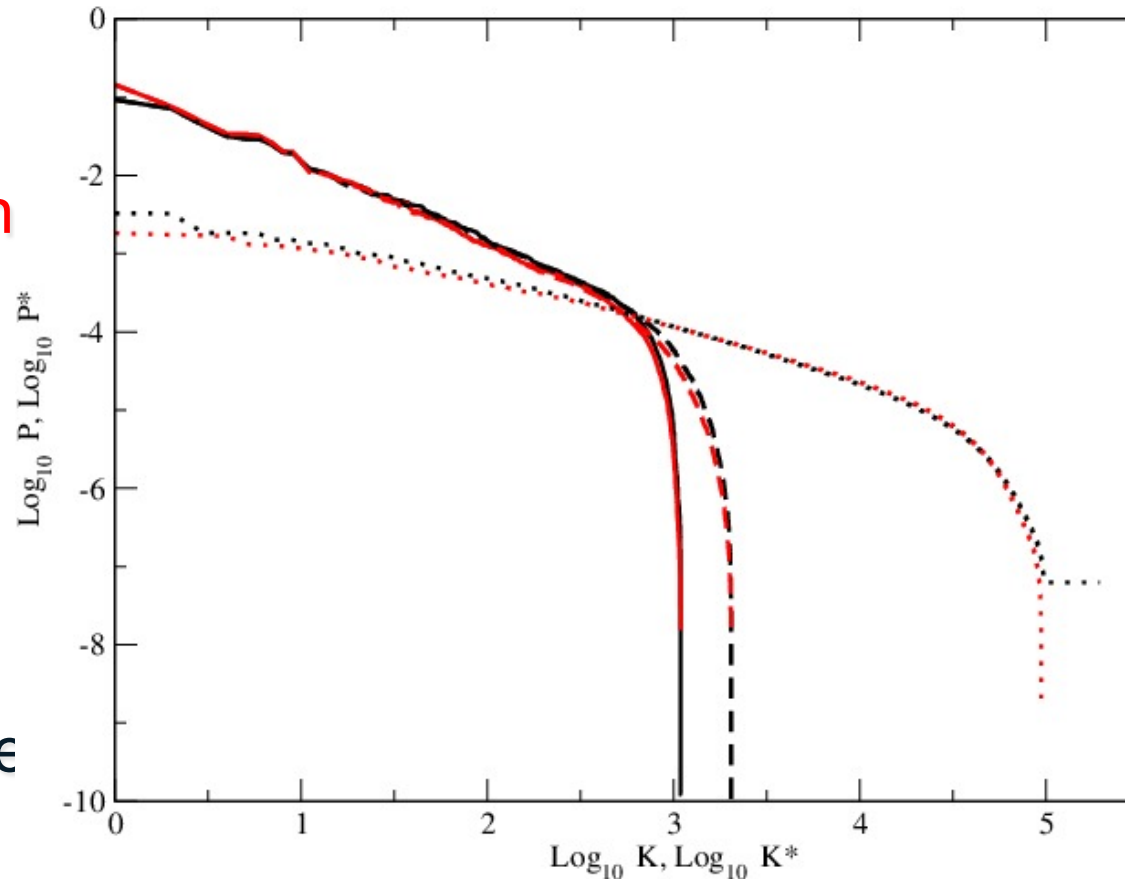
- >Tails of **link distributions** very close to **power-law** with **exponent 1.0** for the integrated distribution.
- >network displays the scale-free property
- >**symmetry between ingoing and outgoing links** is a peculiarity of this network



Normalized integrated distribution of links for $d=5$
Thick solid line is $y=-x$.
Inset: different values of d

Ranking vectors

- >PageRank: ingoing links
- >CheiRank: outgoing links
- >Ranking vectors follow an algebraic law
- >Symmetry between distributions of ranking vectors based on ingoing links and outgoing links.
- >Power law different for the largest network



->Ranking vectors of G. Black is PageRank, Red is CheiRank, Plain line: size 1107, dashed line: size 2051, dotted line: size 193995.

Ranking vectors: correlations

- > **Strong correlations** between **PageRank** and **CheiRank**
- > Strong correlation between moves which open many possibilities of new moves and moves that can follow many other moves.
- > However, the symmetry is far from exact.
- > Correlation **less strong** for **largest network**

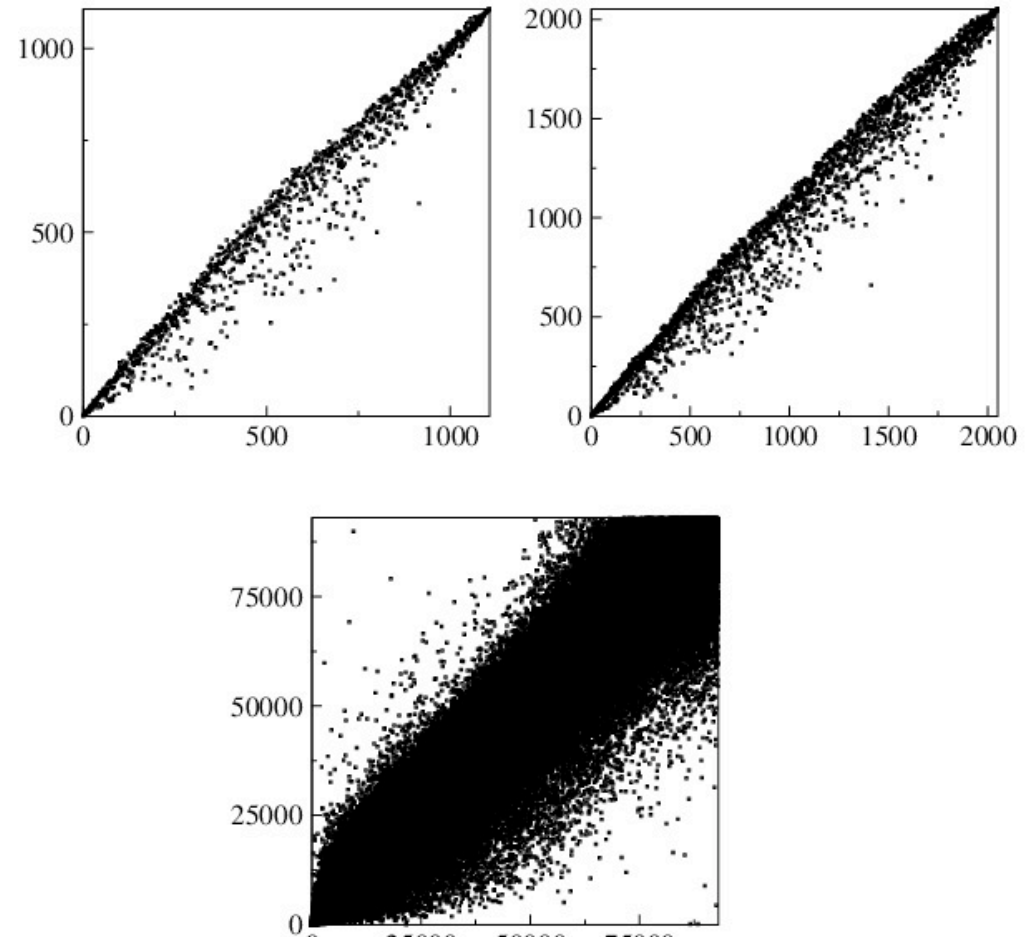


Figure: K^* vs K where K (resp. K^*) is the rank of a vertex when ordered according to PageRank vector (resp CheiRank) for the three networks (sizes 1107, 2051, 193995)

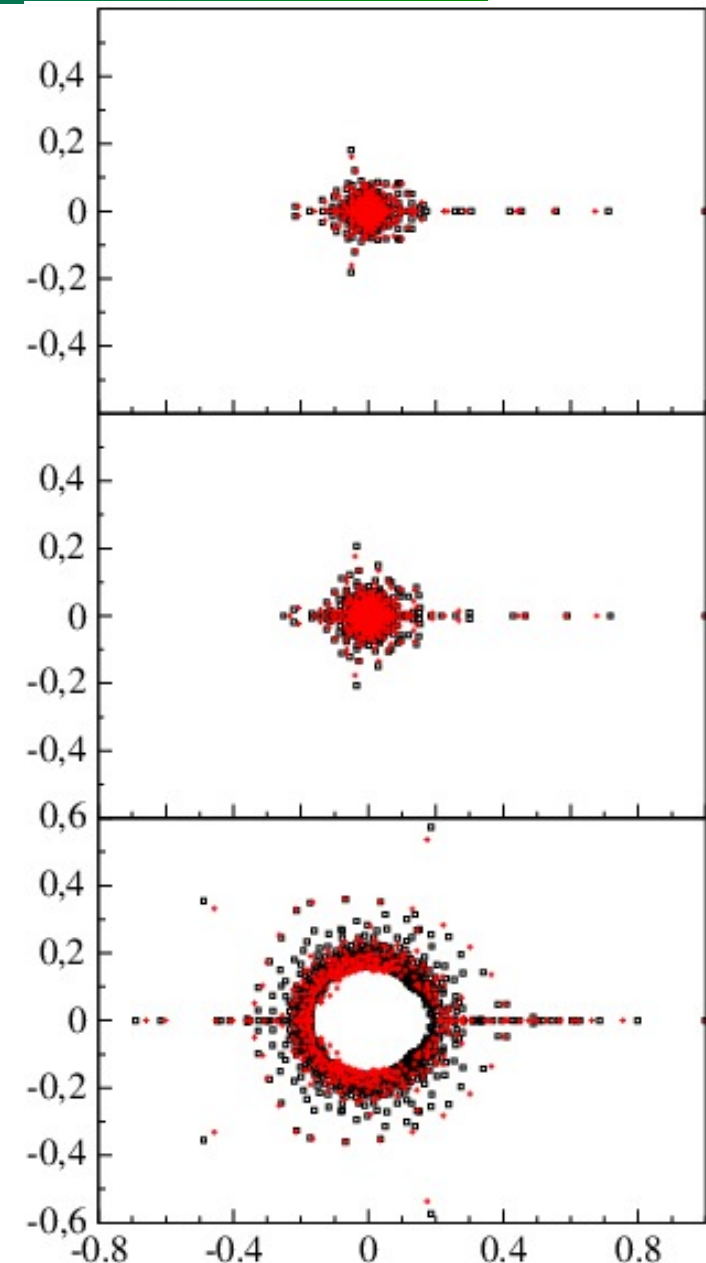
Spectrum of the Google matrix

->For WWW the spectrum is spread inside the unit circle, no gap between first eigenvalue and the bulk
->Here **huge gap** like in **well-connected networks**, with few isolated communities (cf lexical networks).

->**Radius of the bulk** of eigenvalues **changes with size** of network

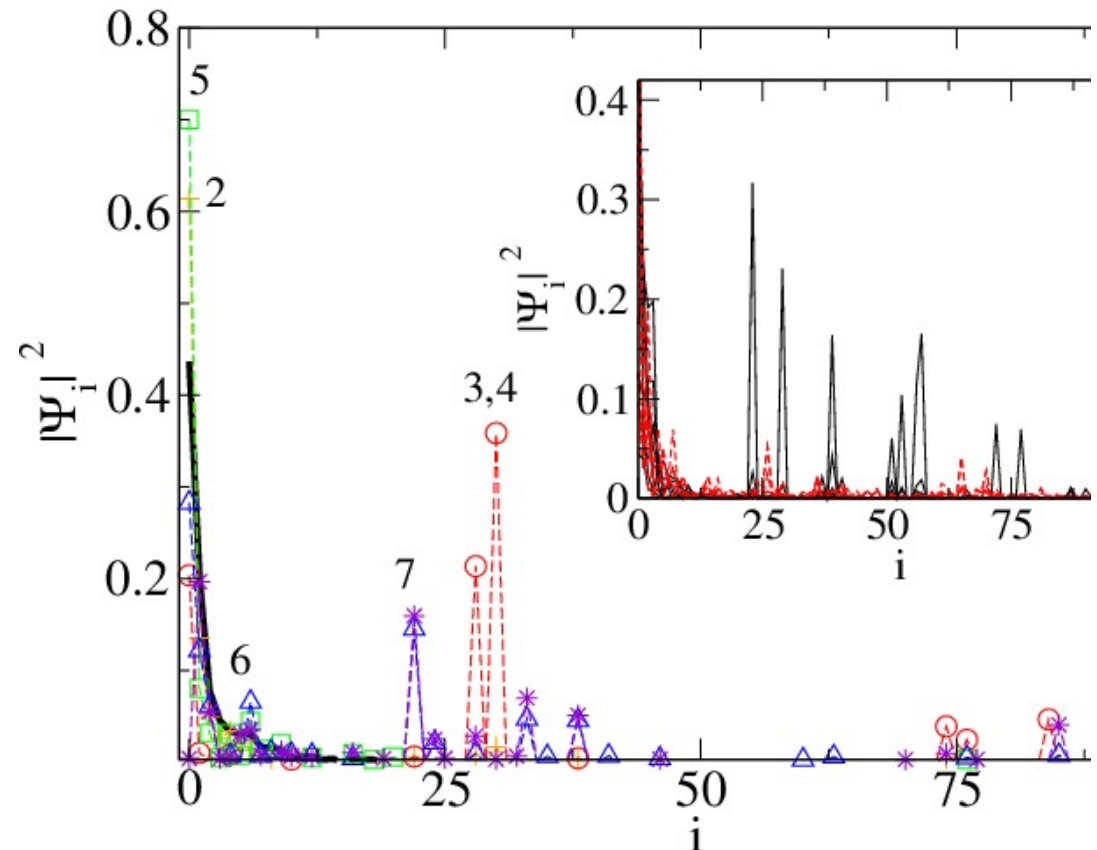
->**More structure** in the networks with **larger plaquettes** which disambiguate the different game paths

Figure: Eigenvalues of G in the complex plane for the networks with 1107, 2051 and 193995 nodes



Eigenvectors of the Google matrix I

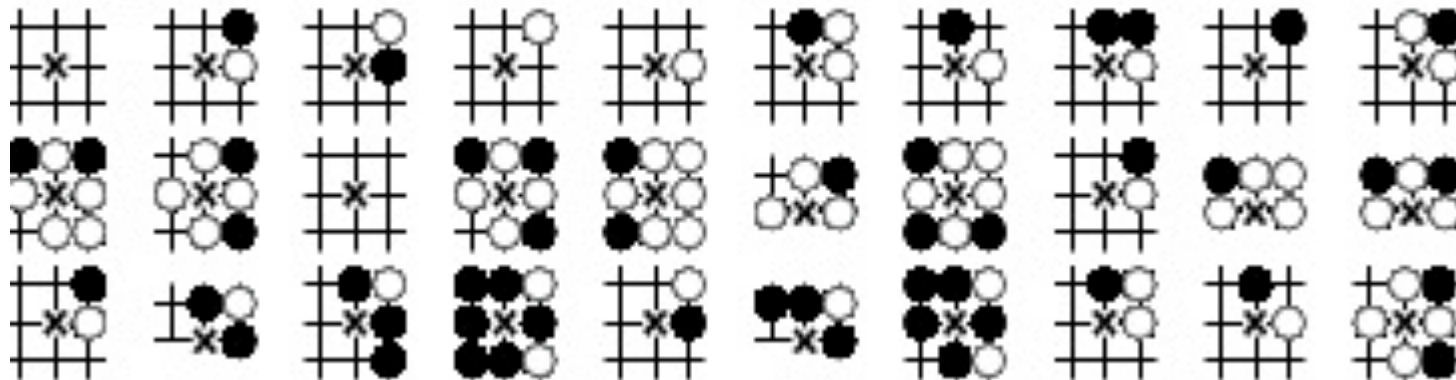
- > Next to leading eigenvalues are important, may indicate the presence of communities of moves with common features.
- > The distribution of the first 7 eigenvectors (Left) shows that they are concentrated on particular sets of moves different for each vector.
- > eigenvectors are different for different tournaments and from professional to amateur
- > much less peaked for randomized network



Moduli squared of the right eigenvectors of the 7 largest eigenvalues of G (network with 1107 vertices). Inset: real games (black) vs random network (red)

Connection with tactical sequences

- > **First eigenvector** is mainly localized on **most frequent moves**
- > **Third one** is localized on moves describing **captures of the opponent's stones**, and part of it singles out the well-known situation of *ko* ("eternity"), where players repeat captures alternately.
- > **The 7th eigenvector** singles out moves which appear to **protect an isolated stone** by connecting it with a chain.



Moves corresponding to the 10 largest entries of right eigenvectors of G for first eigenvalues (PageRank)(top), third one (middle) and seventh one (bottom), Network with 1107 vertices.

Eigenvectors of the Google matrix II

->More complicated groups of moves can be seen in eigenvectors of **larger networks**

->**Systematic method** of grouping them: by antecedent, by correlations between eigenvectors.

Figures: eigenvector for network of size 2051 (bottom) and 193995 (right)

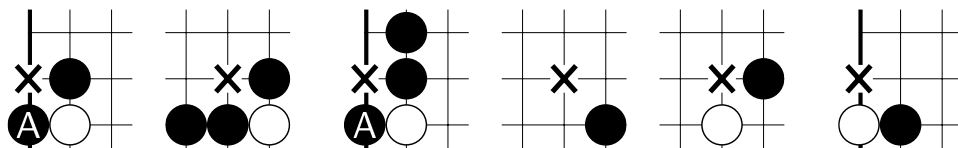


Figure 1: PageRank index : 27, 28, 52, 9, 6, 32,

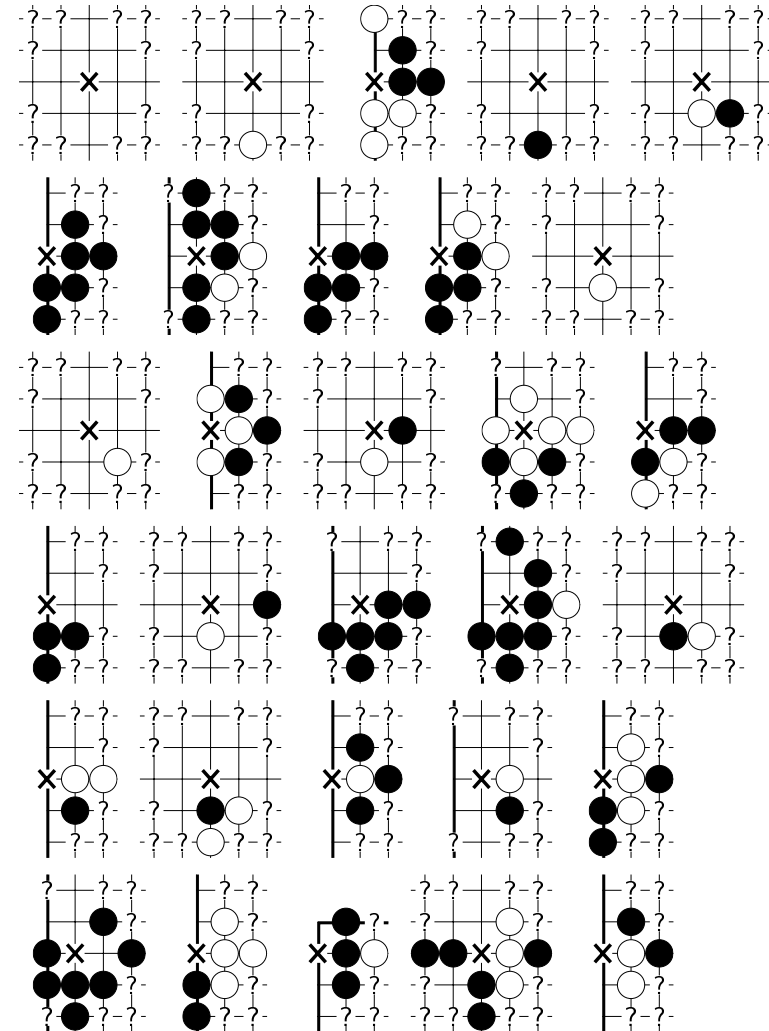
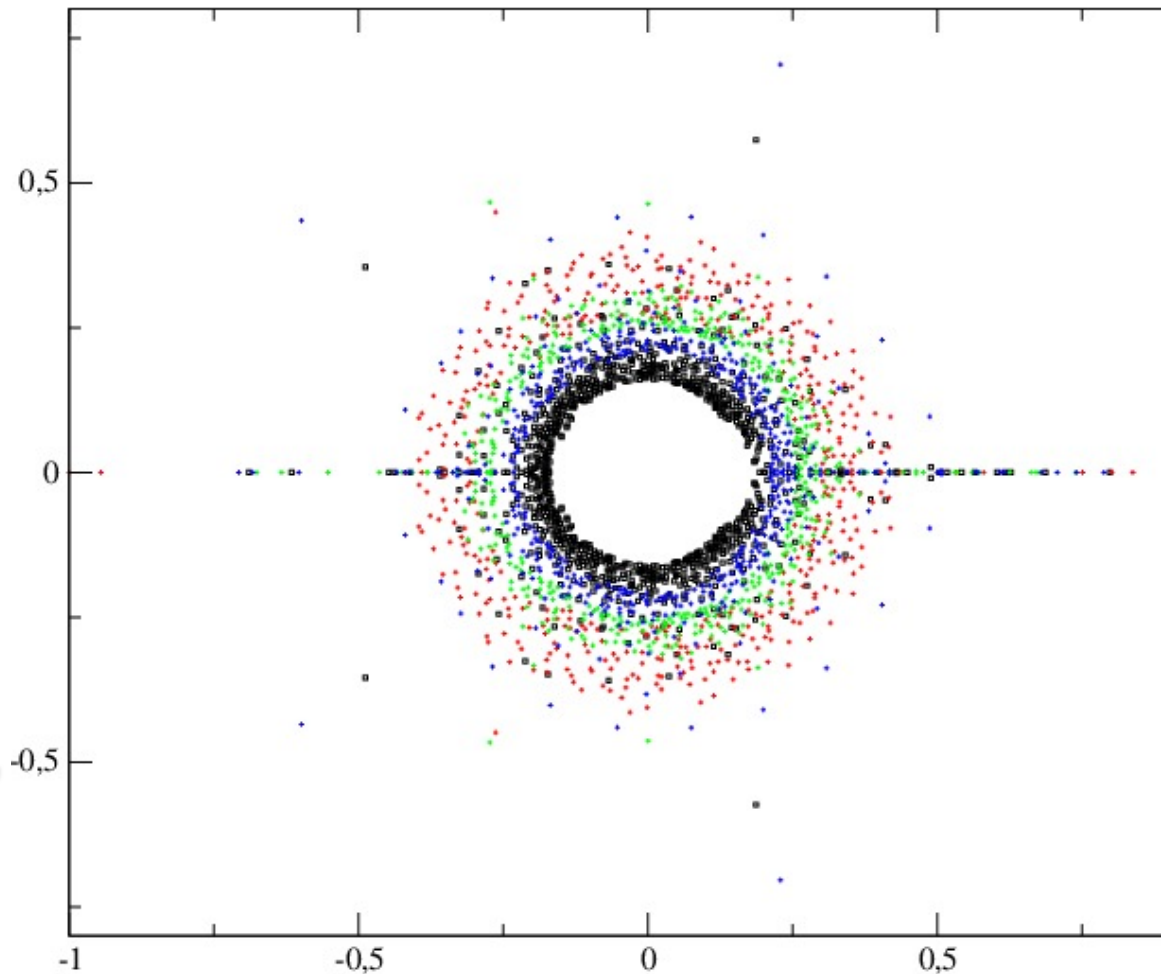


Figure 1: PageRank index : 0, 2, 10726, 1, 3, 35652, 63829, 56615, 45588, 6, 7, 144, 9, 126, 29, 63846, 10, 85819, 75486, 16, 14, 4, 21, 15, 1216, 77223, 1545, 35403, 24208, 22,

Networks for different game phases

- >One can separate the games into **beginning, middle, and end**
- >The three networks are different, with **markedly different** spectra and eigenvectors

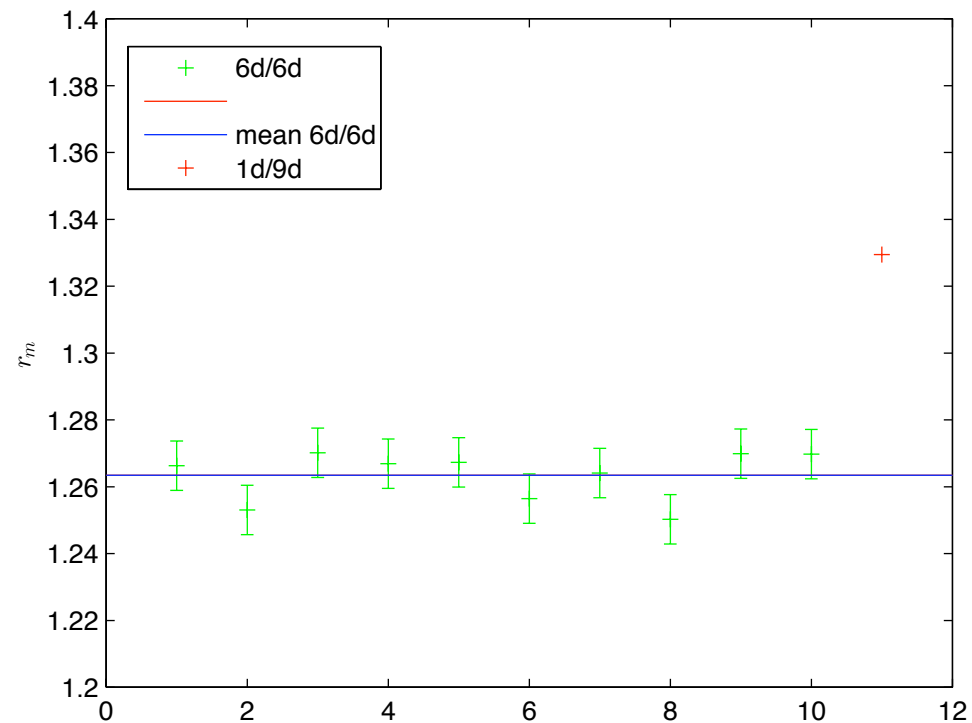
Figure: spectrum for all moves (black), 50 first moves (red), middle 50 (blue) and last 50 (green), Network with 193995 vertices.



Networks for different levels of play

- >One can separate the players by their levels (dans)
- >Differences can be seen between the moves of these players at the network level

Figure: statistical difference between nodes outdegrees for 1dan/9dan and several sets of 6dans/6dans
Network with 193995 vertices.



Conclusion

- > We have built a complex network which describes the **game of go**, one of the most ancient and complex board games.
- > Network structure analyzed with Nadine tools show differences between **professional and amateur games**, **different level** of amateurs, or **phases of the game**.
- > Certain eigenvectors are **localized on specific groups of moves** which correspond to different strategies.
- > The point of view developed should allow to **better modelize** such games and could also help to **design simulators** which could in the future beat good human players.
- > Our approach could be used for **other types of games**, and in parallel shed light on the **human decision making process**.