Classifying Patent Based on their Semantic Content
An empirical exploration into patent text mining

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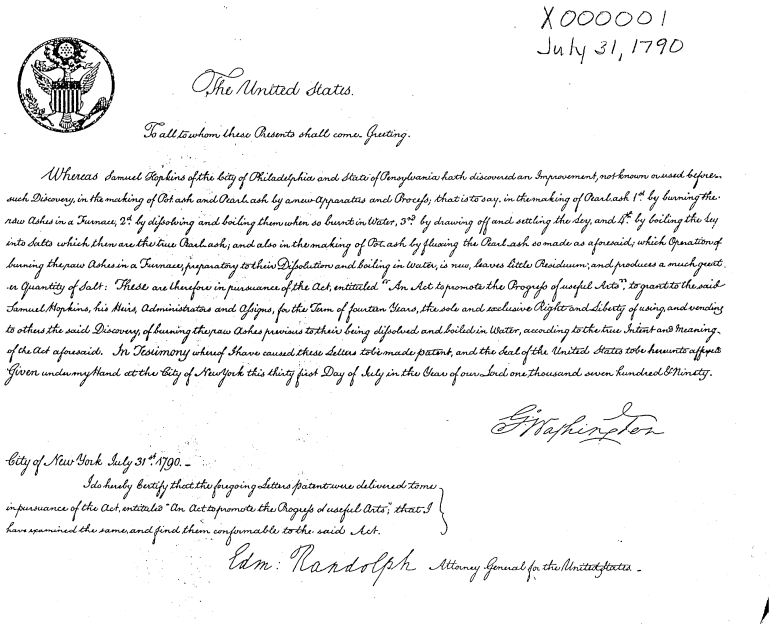
Plan

Motivation

Patenting as a footprint of technology and its coevolution with science and culture [Bais, 2010]



X000001
July 31, 1790

The United States.

To all to whom these Presents shall come. Greeting.

Whereas Samuel Hopkins of the City of Philadelphia and State of Pensylvania hath discovered an Improvement, not known or used before the Discovery, in the making of Pot ash and Pearl ash by a new Apparatus and Process, that is to say, in the making of Pearl ash 1st by burning the raw Ashes in a Furnace, 2d by dissolving and boiling them when so burnt in Water, 3rd by drawing off and settling the ley, and 4th by boiling the ley into Salts which then are the true Pearl ash; and also in the making of Pot ash by fluxing the Pearl ash so made as aforesaid, which Operation of burning the raw Ashes in a Furnace, preparatory to their Dissolution and boiling in Water, is new, leaves little Residuum, and produces a much greater Quantity of Salt: These are therefore in pursuance of the Act, entituled "An Act to promote the Progress of useful Arts", to grant to the said Samuel Hopkins, his Heirs, Administrators and Assigns, for the Term of fourteen Years, the sole and exclusive Right and Liberty of using and vending to others the said Discovery of burning the raw Ashes previous to their being dissolved and boiled in Water, according to the true Intent and Meaning of the Act aforesaid. In Testimony whereof I have caused these Letters to be made patent, and the Seal of the United States to be hereunto affixed. Given under my Hand at the City of New York this thirty first Day of July in the Year of our Lord one thousand seven hundred & Ninety.

G. Washington

City of New York July 31st 1790. –

I do hereby certify that the foregoing Letters patent were delivered to me in pursuance of the Act, entituled "An Act to promote the Progress of useful Arts", that I have examined the same, and find them conformable to the said Act.

Edm: Randolph Attorney General for the United States –

US006285999B1

(12) **United States Patent**
Page

(10) **Patent No.: US 6,285,999 B1**
(45) **Date of Patent: Sep. 4, 2001**

(54) **METHOD FOR NODE RANKING IN A LINKED DATABASE**

(75) Inventor: **Lawrence Page**, Stanford, CA (US)

(73) Assignee: **The Board of Trustees of the Leland Stanford Junior University**, Stanford, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **09/004,827**

(22) Filed: **Jan. 9, 1998**

Related U.S. Application Data

(60) Provisional application No. 60/035,205, filed on Jan. 10, 1997.

(51) **Int. Cl.**[7] **G06F 17/30**

(52) **U.S. Cl.** **707/5**; 707/7; 707/501

(58) **Field of Search** 707/100, 5, 7, 707/513, 1–3, 10, 104, 501; 345/440; 382/226, 229, 230, 231

Craig Boyle "To link or not to link: An empirical comparison of Hypertext linking strategies". ACM 1992, pp. 221–231.*

L. Katz, "A new status index derived from sociometric analysis," 1953, Psychometricka, vol. 18, pp. 39–43.

C.H. Hubbell, "An input–output approach to clique identification sociometry," 1965, pp. 377–399.

Mizruchi et al., "Techniques for disaggregating centrality scores in social networks," 1996, Sociological Methodology, pp. 26–48.

E. Garfield, "Citation analysis as a tool in journal evaluation," 1972, Science, vol. 178, pp. 471–479.

Pinski et al., "Citation influence for journal aggregates of scientific publications: Theory, with application to the literature of physics," 1976, Inf. Proc. And Management, vol. 12, pp. 297–312.

N. Geller, "On the citation influence methodology of Pinski and Narin," 1978, Inf. Proc. And Management, vol. 14, pp. 93–95.

P. Doreian, "Measuring the relative standing of disciplinary journals," 1988, Inf. Proc. And Management, vol. 24, pp. 45–56.

(List continued on next page.)

Motivation

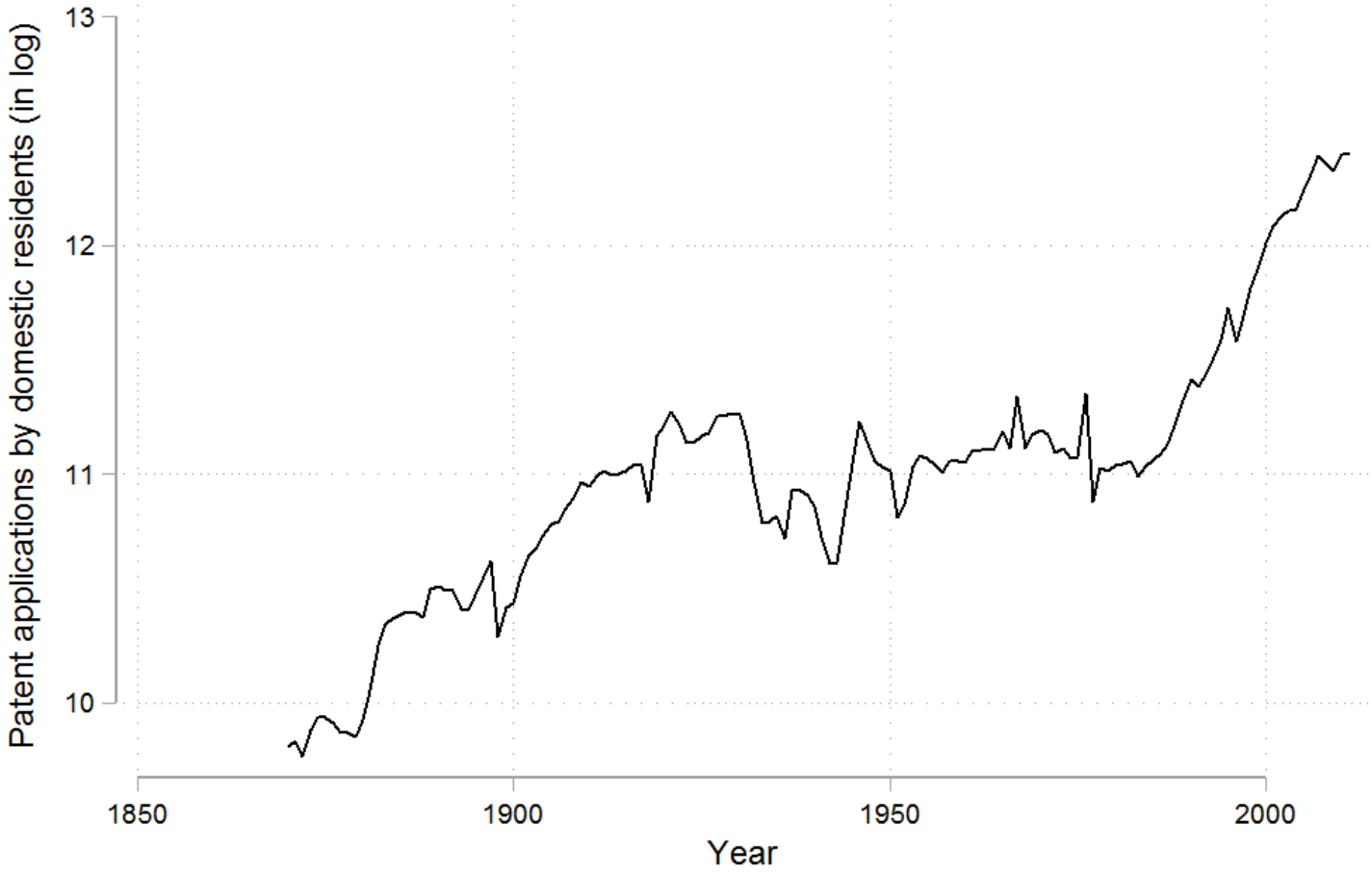


Figure 1: Log number of patent applications per capita at the USPTO. Source : USPTO

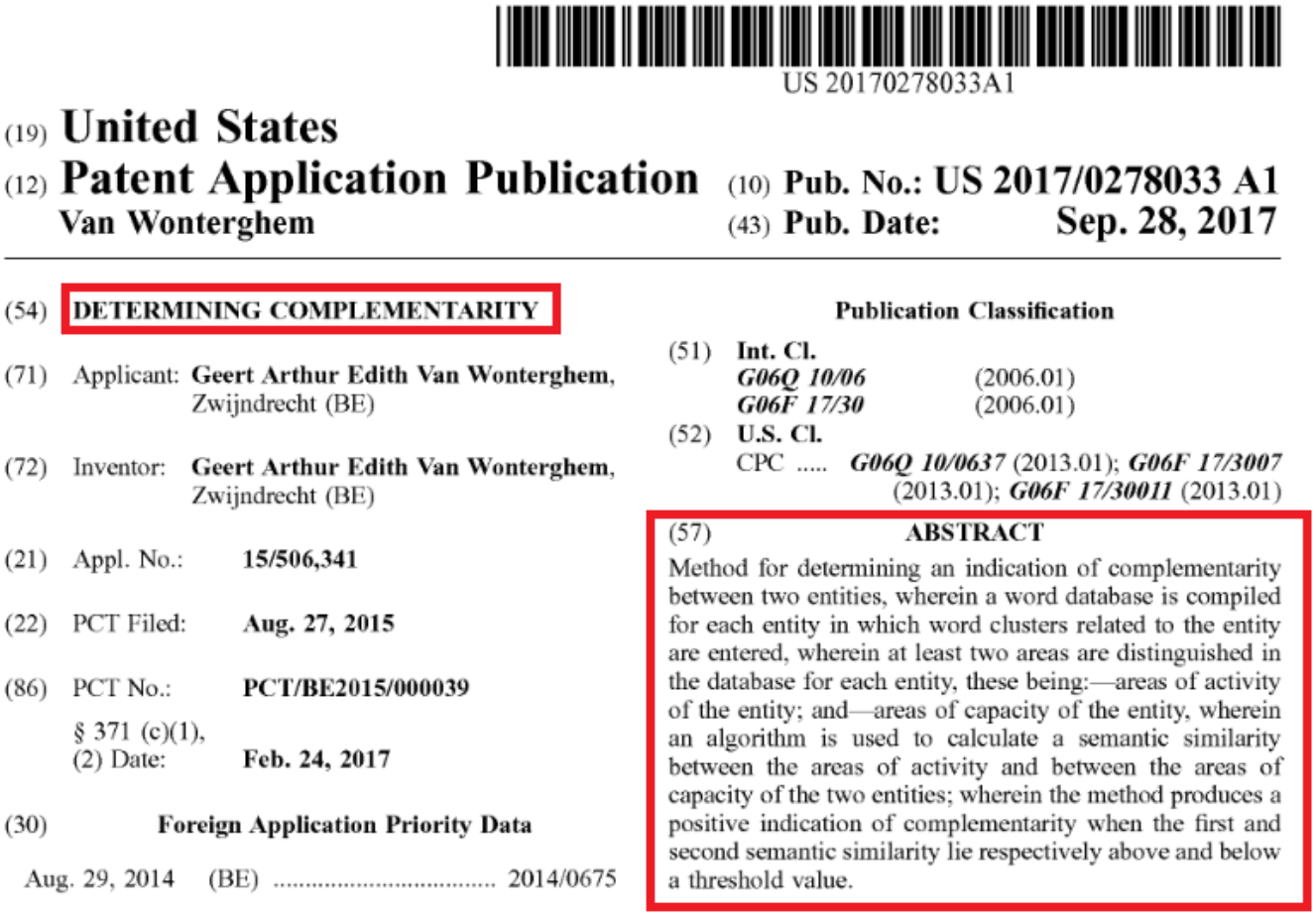
Motivation

What are patents?

- Property rights to an invention (novelty, non-obviousness and industrial applicability). Set the state of the art of a technology.
- Classification system in technology fields (or classes).
- Concept of "Person having ordinary skill in the art": an invention must be sufficiently disclosed in the description of the patent.
- Different realities between countries/IP offices (USPTO, EPO, JPO, CNIPA...).

In practice, patent data are available in the form of a relational database.

Motivation



US 20170278033A1

(19) **United States**

(12) **Patent Application Publication**

Van Wonterghem

(10) **Pub. No.: US 2017/0278033 A1**

(43) **Pub. Date: Sep. 28, 2017**

(54) **DETERMINING COMPLEMENTARITY**

(71) Applicant: **Geert Arthur Edith Van Wonterghem**, Zwijndrecht (BE)

(72) Inventor: **Geert Arthur Edith Van Wonterghem**, Zwijndrecht (BE)

(21) Appl. No.: **15/506,341**

(22) PCT Filed: **Aug. 27, 2015**

(86) PCT No.: **PCT/BE2015/000039**

§ 371 (c)(1),
(2) Date: **Feb. 24, 2017**

(30) **Foreign Application Priority Data**

Aug. 29, 2014 (BE) 2014/0675

Publication Classification

(51) **Int. Cl.**
G06Q 10/06 (2006.01)
G06F 17/30 (2006.01)

(52) **U.S. Cl.**
CPC ***G06Q 10/0637*** (2013.01); ***G06F 17/3007*** (2013.01); ***G06F 17/30011*** (2013.01)

(57) **ABSTRACT**

Method for determining an indication of complementarity between two entities, wherein a word database is compiled for each entity in which word clusters related to the entity are entered, wherein at least two areas are distinguished in the database for each entity, these being:—areas of activity of the entity; and—areas of capacity of the entity, wherein an algorithm is used to calculate a semantic similarity between the areas of activity and between the areas of capacity of the two entities; wherein the method produces a positive indication of complementarity when the first and second semantic similarity lie respectively above and below a threshold value.

Figure 2: Example of patent front page. Source : USPTO

Patents and text-mining

- Main usage: matching between patents and firms/inventors
- Used in the search of prior-art/litigation
- Technology mapping

Why study patents ?

→ Although imperfect, patents are the most commonly used measure of innovation in economics.
→ Applied Epistemology : particular case of the ecology and evolution of knowledge; diffusion of knowledge.

Examples :

- [Griliches, 1998]: patent as an economic indicator
- [Youn et al., 2015] interaction between technological fields ; combinatorial nature of inventions
- [Bruck et al., 2016] citation network analysis to detect emerging research front
- [Gerken and Moehrle, 2012] [Tseng et al., 2007] semantic analysis (remains limited to specific fields and time windows)

A large scale semantic insight into USPTO database

Proposed approach

Complement existing patent office classifications using patent semantic content
Why?: more endogenous, flexible and informative (?). And comparison with *technological* classification to detect outliers.

Takeaway results

$\rightarrow$ *An endogenous semantic classification is constructed for the full USPTO abstracts and titles, 1976-2012*

$\rightarrow$ *Information carried in the semantic classification is complementary to the technological classification*

Plan

Descriptive statistics

Summary statistics for the USPTO database between 1976 and 2013

- 4,666,365 utility patents from 1976 to 2013
- 70,000 in 1976 to 278,000 in 2013
- 38,756,292 citation links (84% of within-class citations)
- 270,877 patents with no citations 5 years next to publication

Does this mean that innovation is 4 time larger en 2013 than in 1976...
Not necessary. Although definitely more specialized.

Number of inventors

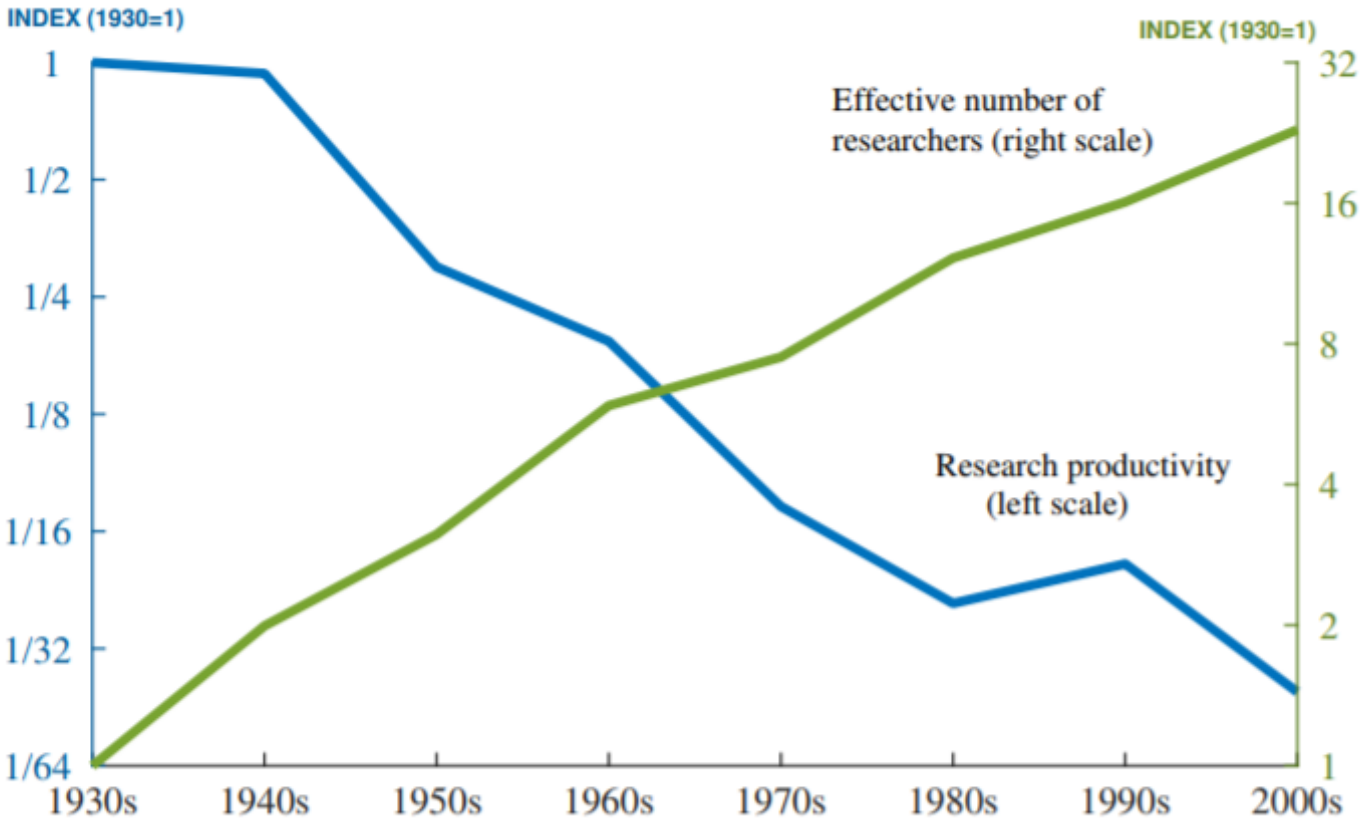


Figure 3: Evolution of number of researchers and productivity of R&D. Source: Bloom et al. (2017)

Inventors per patent

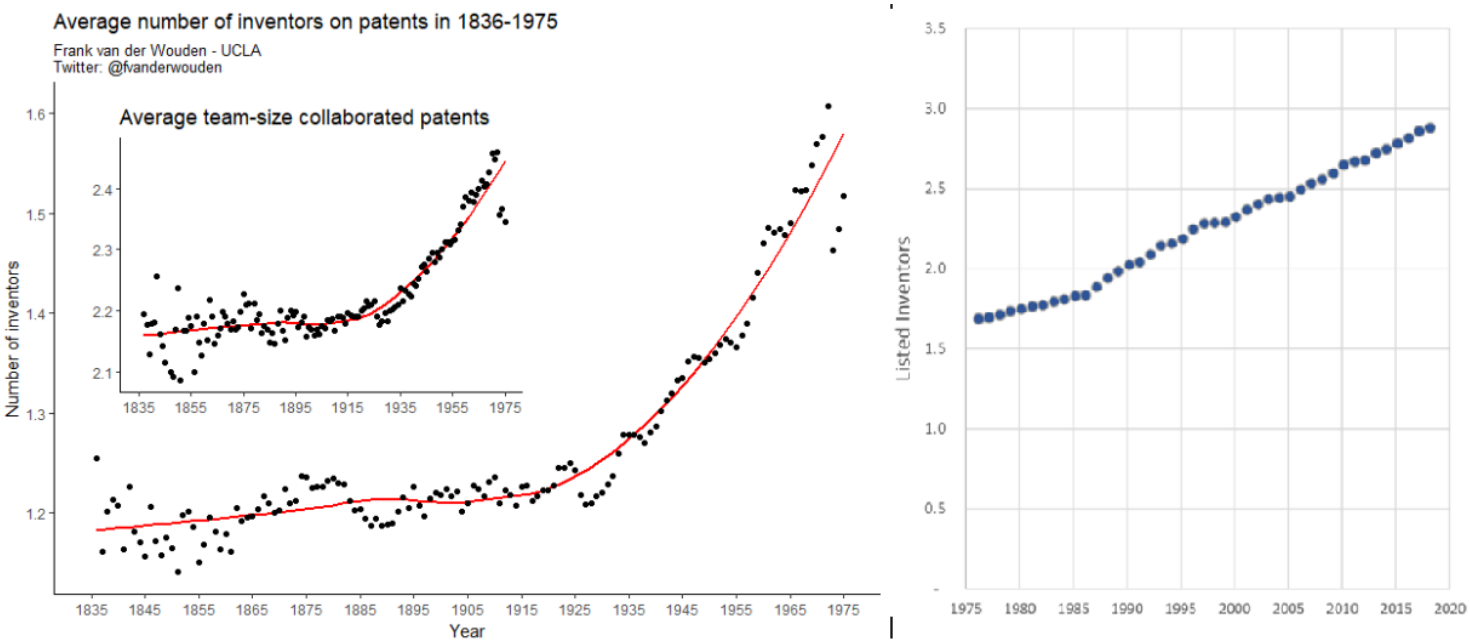


Figure 4: Average number of inventors per patent. Source: USPTO.

(It was 1.2 in 1900). Ideas are getting harder to find?

Database construction

Construction of a Database from US Patent and Trademark Office redbook 1976-2012 (full patent description), which provide raw data but on separate files and different formats

Data Collection Procedure

- Automatic download of raw data file
- Parsing depending on format : `dat` or `xml` (varying schema)
- Uniformisation and storing in MongoDB

$\rightarrow$ 4,666,365 patents with text data (abstract); dated by application date (current state of knowledge, differs from the granted date which implies review processes and an exogenous intervention)

Plan

Extracting relevant n-grams

Text-mining in python with `nltk` *[Bird, 2006]*, method adapted from [Chavalarias and Cointet, 2013]. Advantage over LDA: scalability and flexibility

- Parsing and tokenizing / pos-tagging (word functions) / stemming with `nltk`
- Selection of potential *n-grams* (with $1 \leq n \leq 3$) with the rule $\bigcap\{NN \cup VBG \cup JJ\}$
- Database insertion for instantaneous use (several days $\rightarrow$ 1min)
- Estimation of *n-grams* relevance, following co-occurrences statistical distribution (*termhood* score as chi-2 score)

Estimation of n-gram relevance

- Termhood-based selection of a fixed number of keywords $K_W = 100,000$ (*difficulty to select terms in general*) Definition
- Estimation on temporal moving windows $[t - T_w; t]$ (fixed to $T_W = 4y$ after sensitivity analysis)
- Filtering of network edge (parameter θ_w), with an additional exogenous control by technological class keyword concentration to filter nodes (parameter θ_c)
- Low sensibility to the length of the time window for the network structure Sensitivity analysis

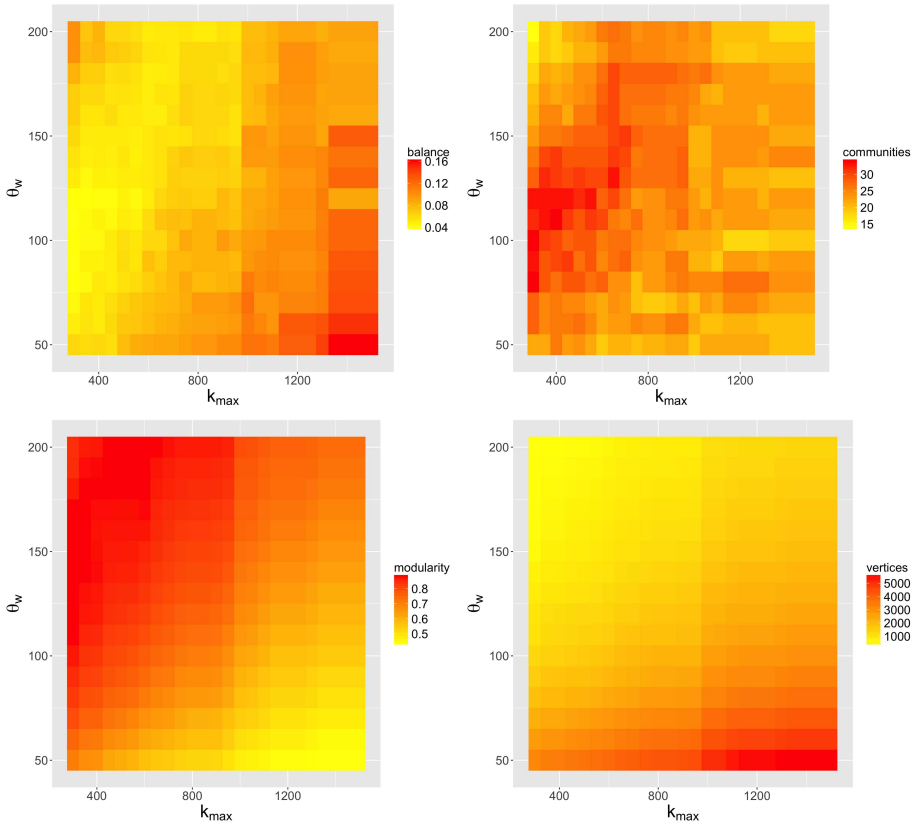
Technical aspects

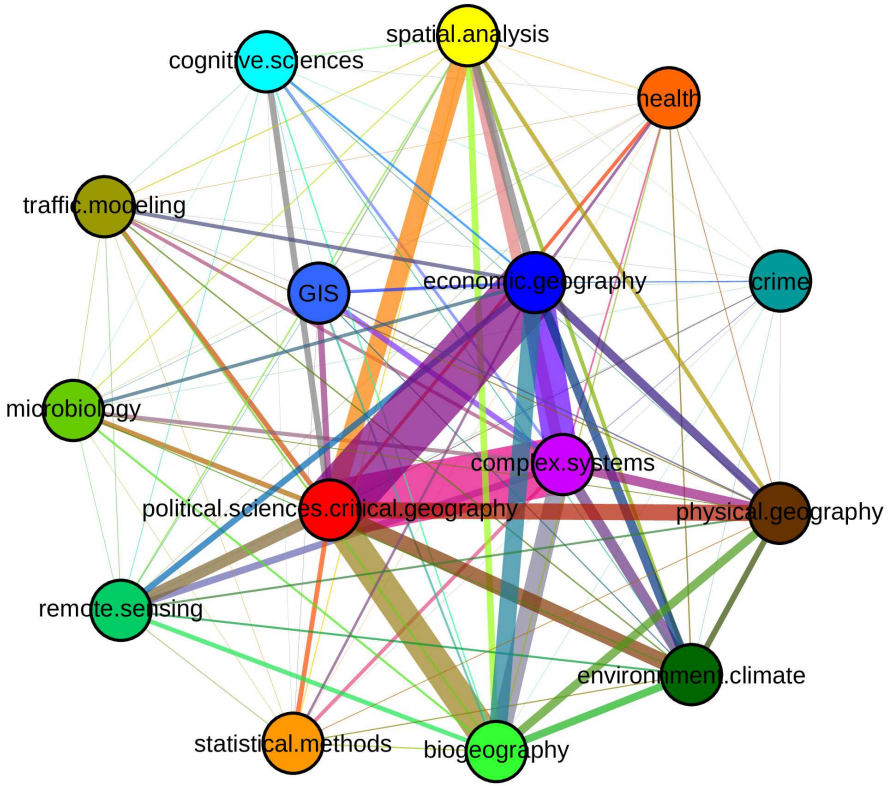
$\rightarrow$ Temporal complexity: $\mathcal{O}(N_P)$ for keyword extraction and co-occurrences (constant I^2_{max}); parallelization on a 60 cores server for a "reasonable" computation time.

$\rightarrow$ Memory complexity: co-occurrence matrices in $\mathcal{O}(K^2_W)$; necessitates around 600Go RAM when parallelized.

$\rightarrow$ Database management: MongoDB (nosql suited to big data).

An application of the method to a scientific corpus

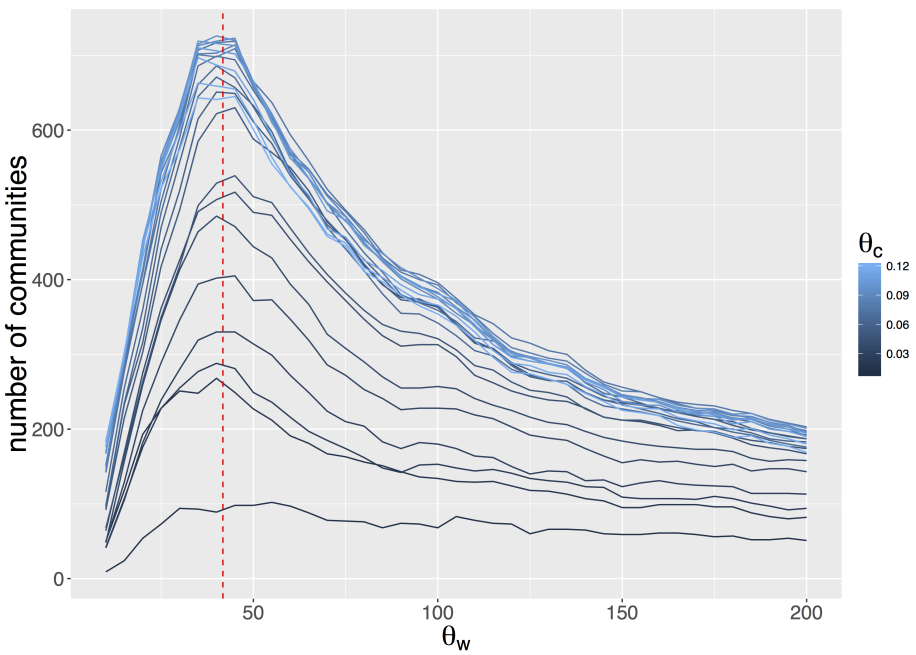


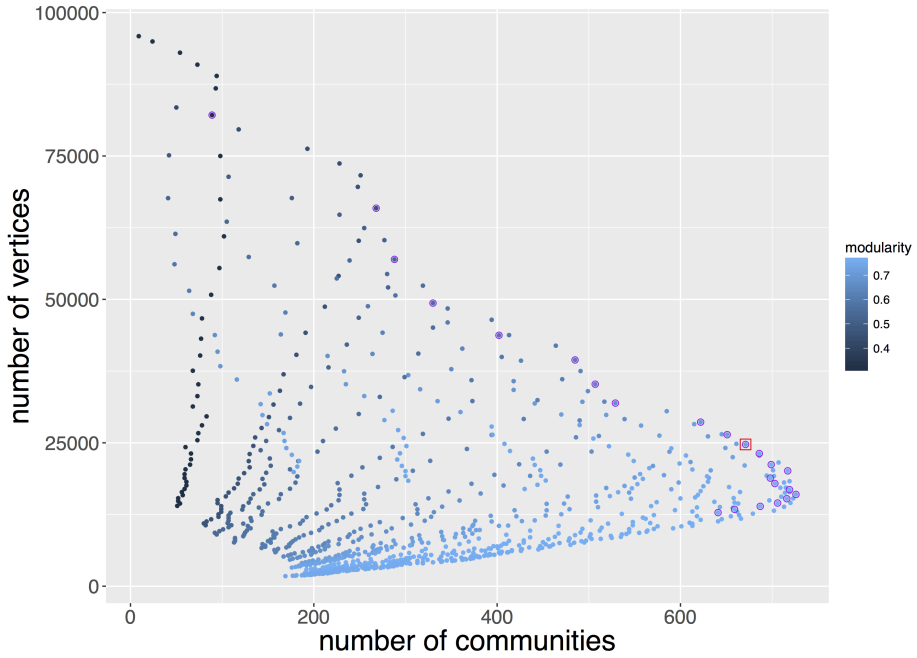


The method has been applied to a scientific corpus; adaptation of optimization procedures as the topological structure is different. [Raimbault, 2017]

Plan

Optimizing network structure

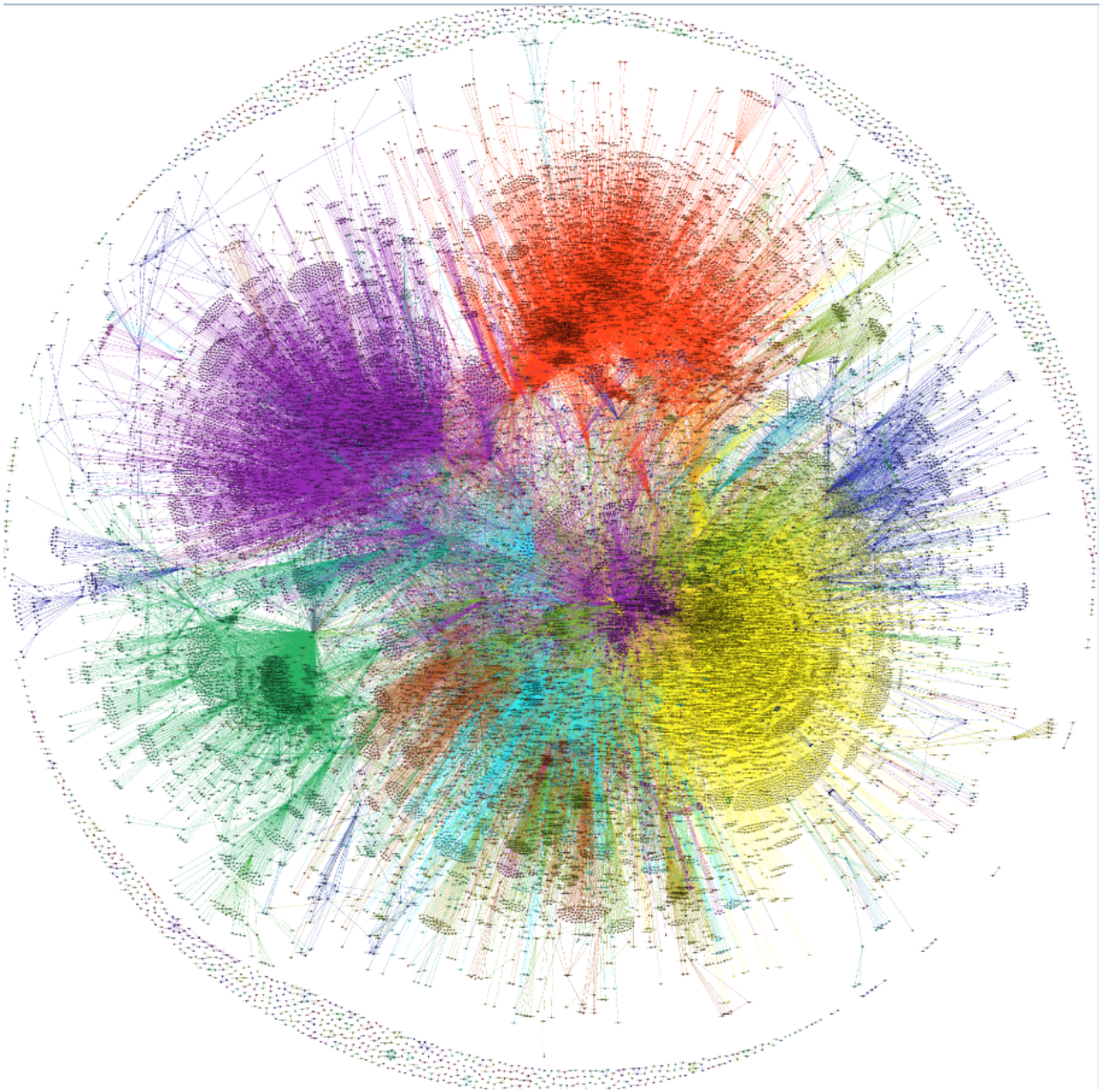




Pareto optimization on cutoff parameters with the objectives of modularity, size and number of communities

Sensitivity analysis

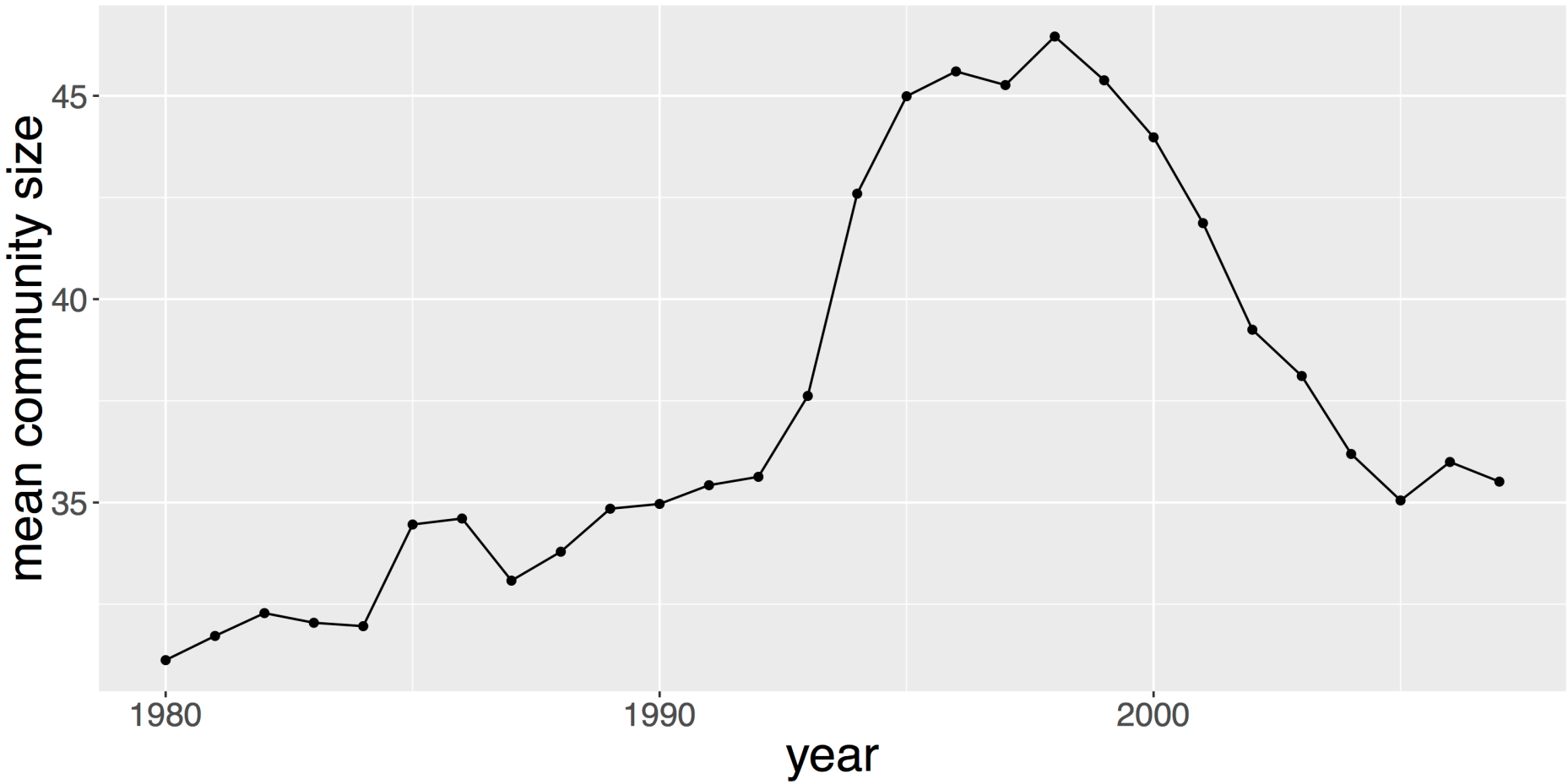
Semantic network visualization (example for 2000-2004)



Classes Examples (2000-2004)

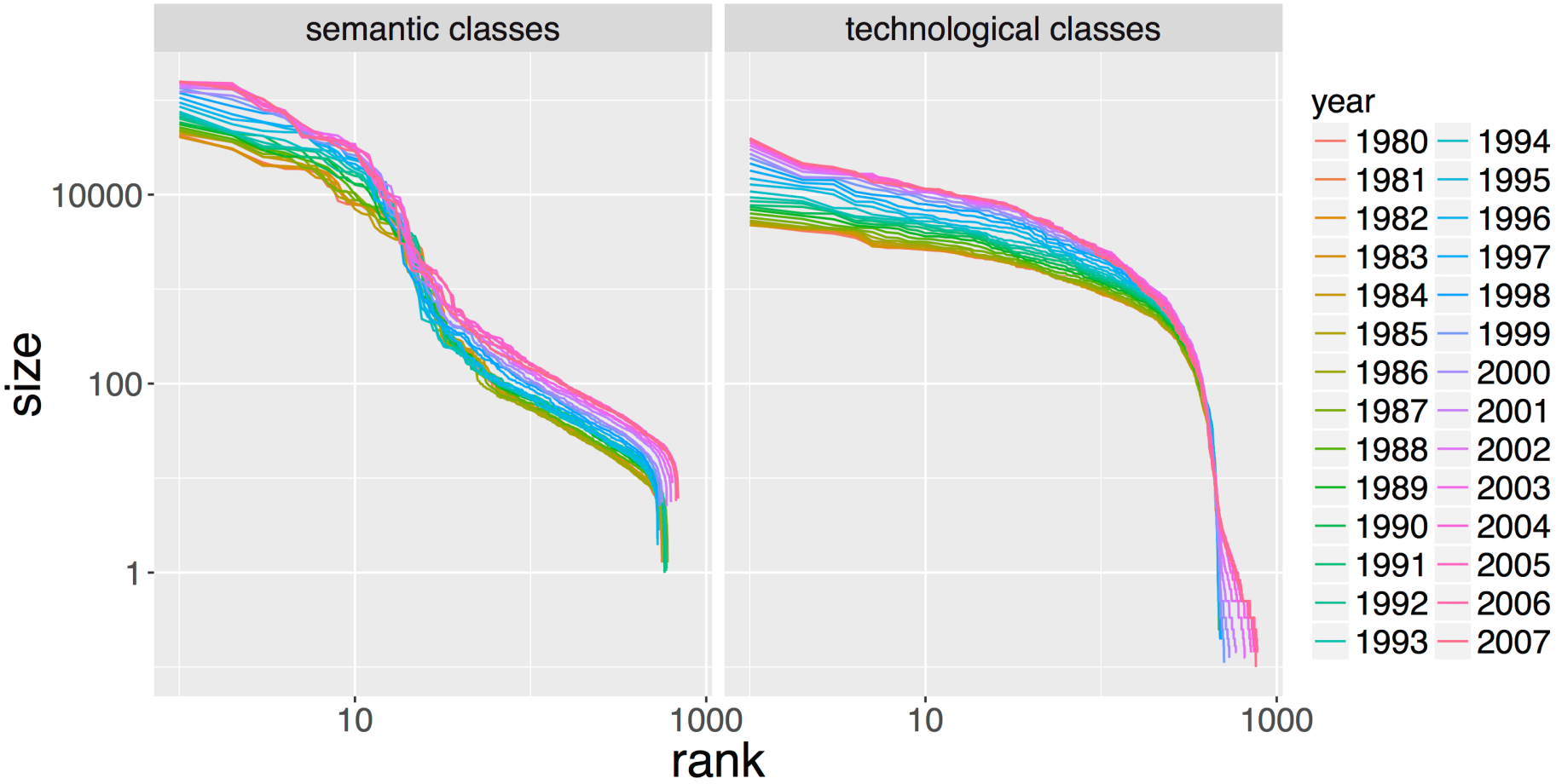
- Memory devices : `semiconductor memori devic; memori cell plural; memori cell transistor; layer ferroelectr`
- Chemical analysis : `time-of-flight mass spectromet; chromatograph column; ion trap mass`
- Particular steel : `martensit; austenit stainless steel`
- Laser : `emit laser beam; vertic caviti surfac; vcsel`
- Sewing : `circular knit machin; stitch; sew machin; embroideri`
- Lithography : `lithograph mask; project beam radiat; heat-sensit; planograph print plate`
- Tobacco : `cigarett filter; cigarett pack; tobacco; tobacco rod`

Size of classes



A peak in average class size around 1998

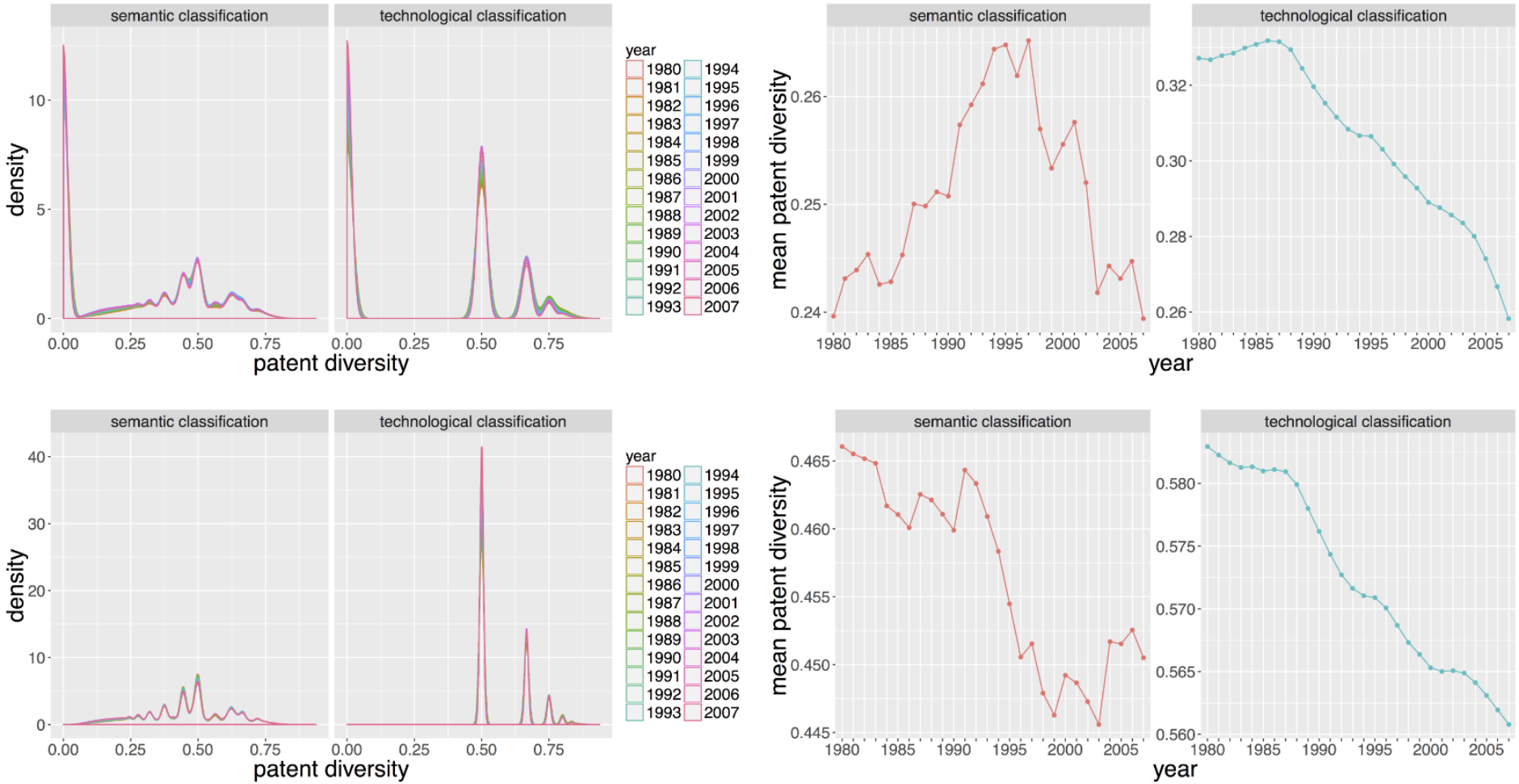
Hierarchical class structure



Fat-tail distribution of class size for both classification, closer to a power-law for semantic classes

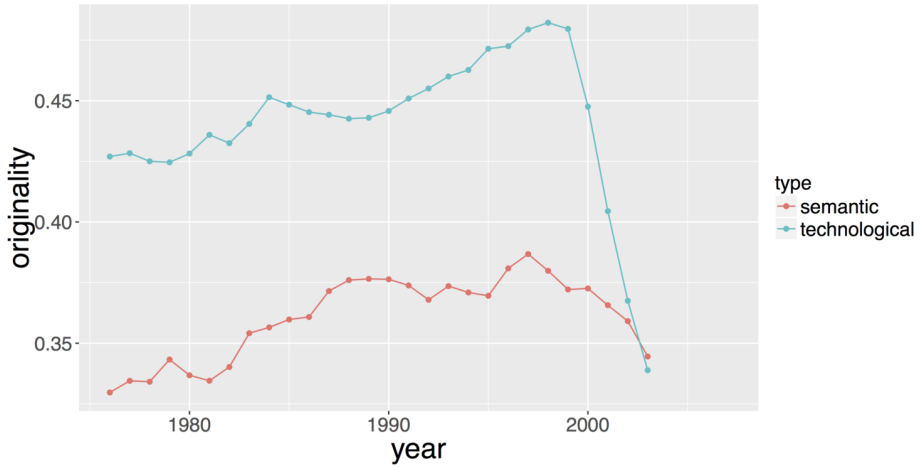
Evolution of patent diversities

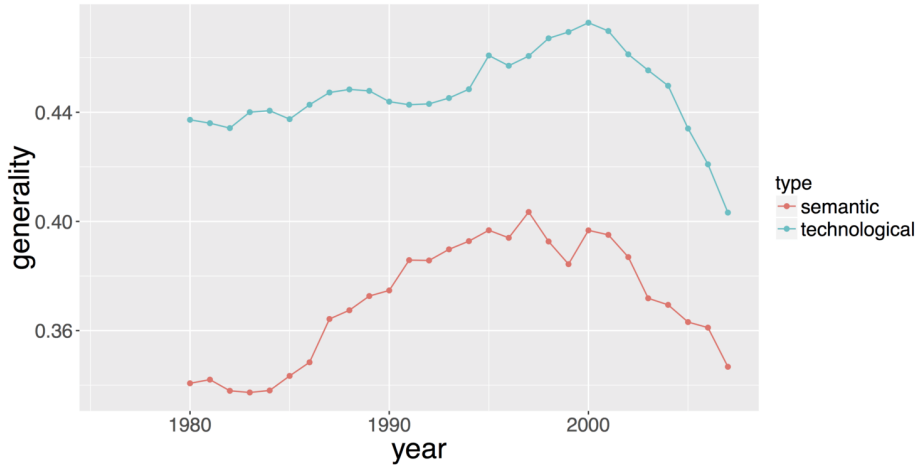
Back



General increase in average invention specialization seen both for semantic and technological; semantic regime shift in 1996

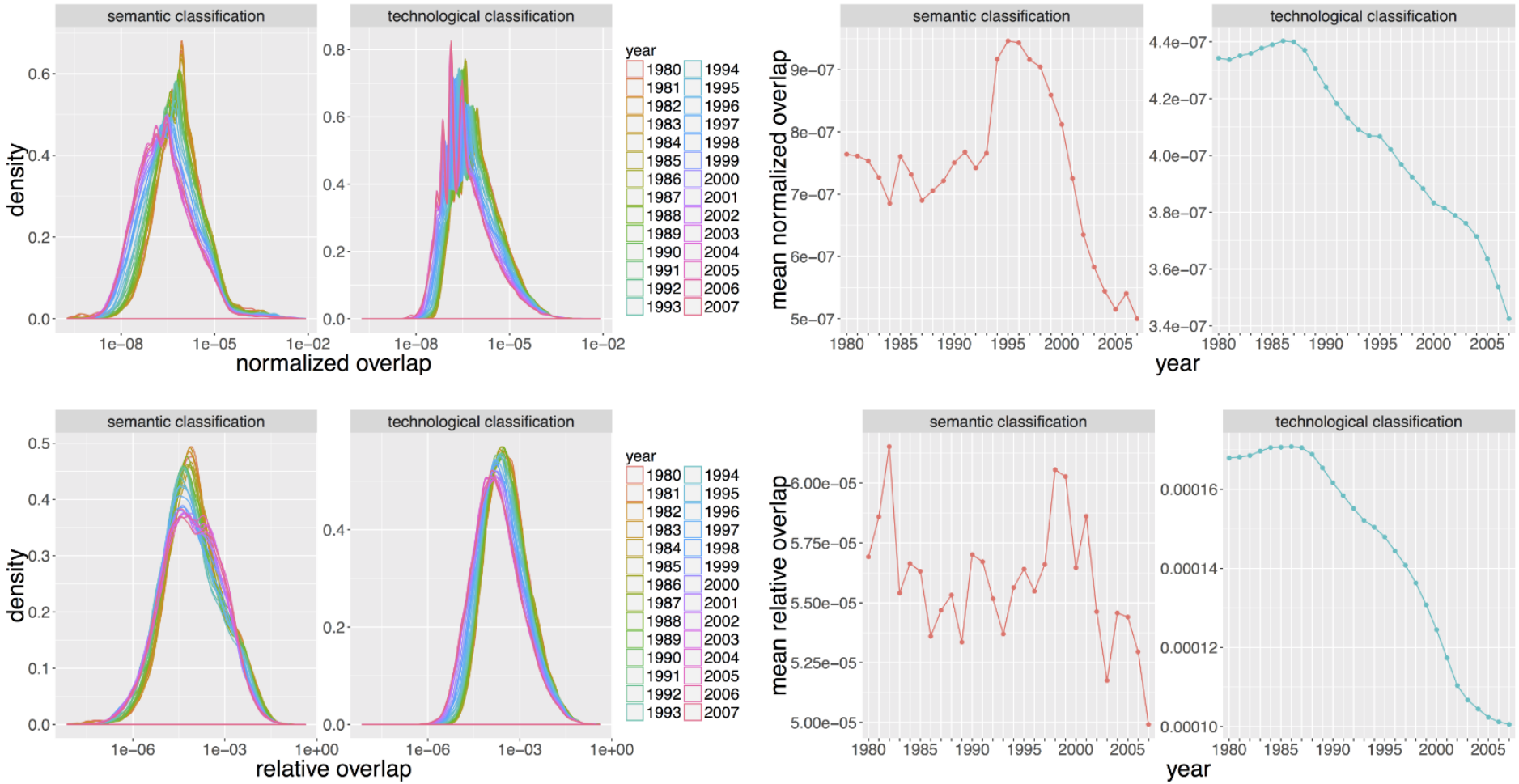
Originality and generality measures





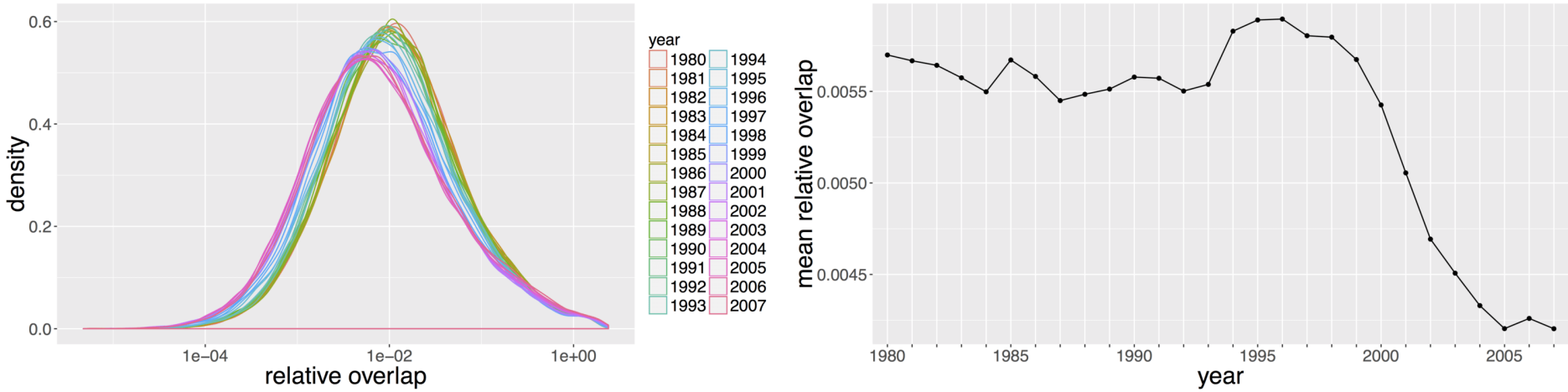
Systematically lower originality and generality (citation-based measures) for the semantic classification (consistent with the higher modularity shown thereafter).

Interaction between classes: intra-classification overlaps



Increased technological specialization; qualitative regime shift confirmed in 1996 for the semantic classification

Inter-classification overlaps

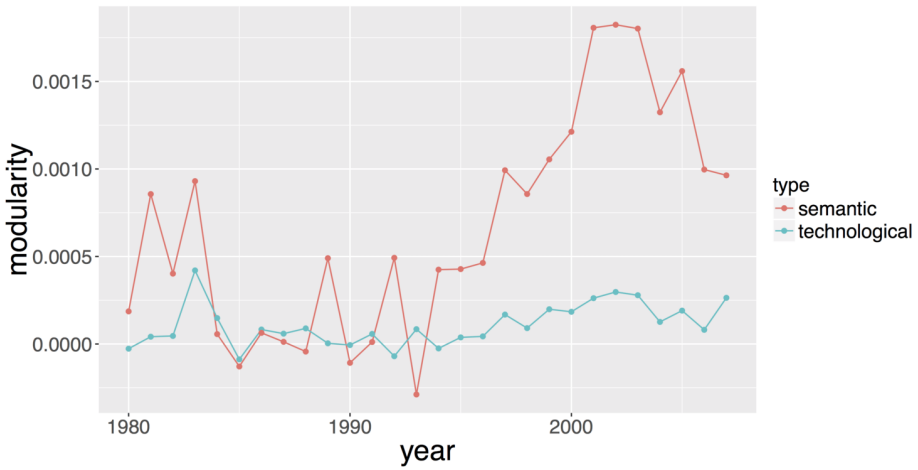


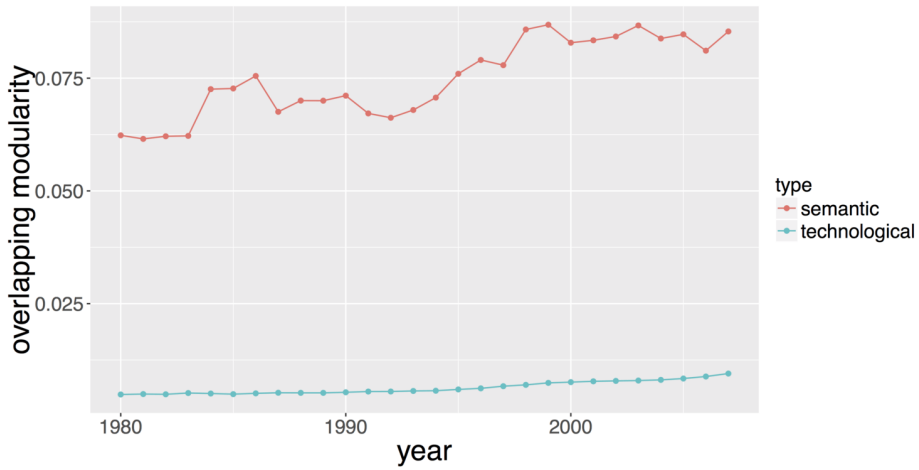
Constant then decreasing average overlap between technological and semantic classes; confirms the change in nature of inventions around 1996.

$\rightarrow$ an impact of new information technologies (regarding knowledge production: from expert and contextualized to automatized search in references e.g.) ? Linked to structural changes in economy (increase in firm concentration since 90s) ?

Modularity of classifications

Definition





Semantic classification is more significant regarding the structure of the citation network, both for single-class and multi-class modularities (confirmed statistically using a simple Stochastic Block Model).

Stochastic Block Modeling to evaluate consistency of classifications

- We complete the analysis by developing a statistical model aiming at quantifying performance of both technological and semantic classification systems
- Intuitively, we look at within class citations proportion (for both technological and semantic approaches)
- Question: is the semantic classification better at predicting future within class citations?
  $\longrightarrow$ short answer is yes.

Summary of outcomes

- A clean redbook
- Semantic and technological classification for each patent
- Network based measure of centrality for each patent

Most importance insight: semantic classification does carry some information beyond what the technological classification provides.

Plan

Possible developments

Direct

- Look at the correlation between patent quality indicators and centrality indices.
- Use patent-firm matching to study a *firm-level* semantic network.
- Extending the analysis to other patent offices (EPO/JPO).

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Economic

- Linking semantic measures to values of firms
- Can semantic proximity helps understand M&A?
- Firms trajectories in relation to their life-cycle

Possible developments

Direct

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Economic

- Linking semantic measures to values of firms
- Can semantic proximity helps understand M&A?
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Technology

- Measure of complementarity between technology?
- Possible application to detection of emerging research fronts
- An interactive exploration of semantic content?

Other projects

At the interface of geography and economics

$\rightarrow$ Quantifying the diffusion of innovation in urban systems, and its co-evolution with the socio-economic structure

Possible developments in other disciplines

$\rightarrow$ Agent-based modeling of interactions between technologies

$\rightarrow$ Full-text mining and history of technology

Conclusion

→ A quantitative epistemology insight into the evolution of technology

→ Towards reflexive approaches in science and technology to ease technological transfer / foster the co-evolution between the two ?

Open repository at `https://github.com/JusteRaimbault/PatentsMining`

Raw database at `http://dx.doi.org/10.7910/DVN/BW3ACK`

Semantic classification database at `http://dx.doi.org/10.7910/DVN/ZULMOY`

Acknowledgments: thanks to ISC-PIF for access to the computation infrastructure.

Reserve slides

Filtration measures

Back

1. *Unithood: n-gram specific frequency-based filtration ($4 \cdot K_W$ keywords)*

$$u_i = f_i \cdot \log(1 + l_i)$$

2. *Termhood: chi-square statistic for the uniformity of co-occurences*

$$t_i = \sum_{j \neq i} \frac{(M_{ij} - \sum_k M_{ik} \sum_k M_{jk})^2}{\sum_k M_{ik} \sum_k M_{jk}}. \quad (1)$$

3. *Edge weight filtration with a threshold of $\theta_w = \theta_w^{(0)} \cdot N_P$*

4. *Node filtration with a threshold θ_c on technological class concentration given by*

$$c_{tech}(s) = \sum_{j=1}^{N^{(tec)}} \frac{k_j(s)^2}{(\sum_i k_i(s))^2}$$

Patent measures

Back

Diversity

$$D_i^{(z)} = 1 - \sum_{j=1}^{N^{(z)}} p_{ij}^2, \text{ with } z \in \{tec, sem\}$$

Originality and Generality

$$O_i^{(z)} = 1 - \sum_{j=1}^{N^{(z)}} \left(\frac{\sum_{i' \in I_i} p_{i'j}}{\sum_{k=1}^{N^{(z)}} \sum_{i' \in I_i} p_{i'k}} \right)^2 \text{ and } G_i^{(z)} = 1 - \sum_{j=1}^{N^{(z)}} \left(\frac{\sum_{i' \in \tilde{I}_i} p_{i'j}}{\sum_{k=1}^{N^{(z)}} \sum_{i' \in \tilde{I}_i} p_{i'k}} \right)^2$$

Definition of modularities

Back

Directed simple modularity [Nicosia et al., 2009]

$$Q_d^{(z)} = \frac{1}{N_P} \sum_{1 \leq i,j \leq N_P} \left[A_{ij} - \frac{k_i^{in} k_j^{out}}{N_P} \right] \delta(c_i, c_j),$$

Multi-class modularity:

$$Q_{ov}^{(z)} = \frac{1}{N_P} \sum_{c=1}^{N^{(z)}} \sum_{1 \leq i,j \leq N_P} \left[F(p_{ic}, p_{jc}) A_{ij} - \frac{\beta_{i,c}^{out} k_i^{out} \beta_{j,c}^{in} k_j^{in}}{N_P} \right],$$

where

$$\beta_{i,c}^{out} = \frac{1}{N_P} \sum_j F(p_{ic}, p_{jc}) \text{ and } \beta_{j,c}^{in} = \frac{1}{N_P} \sum_i F(p_{ic}, p_{jc}).$$

Network sensitivity analysis

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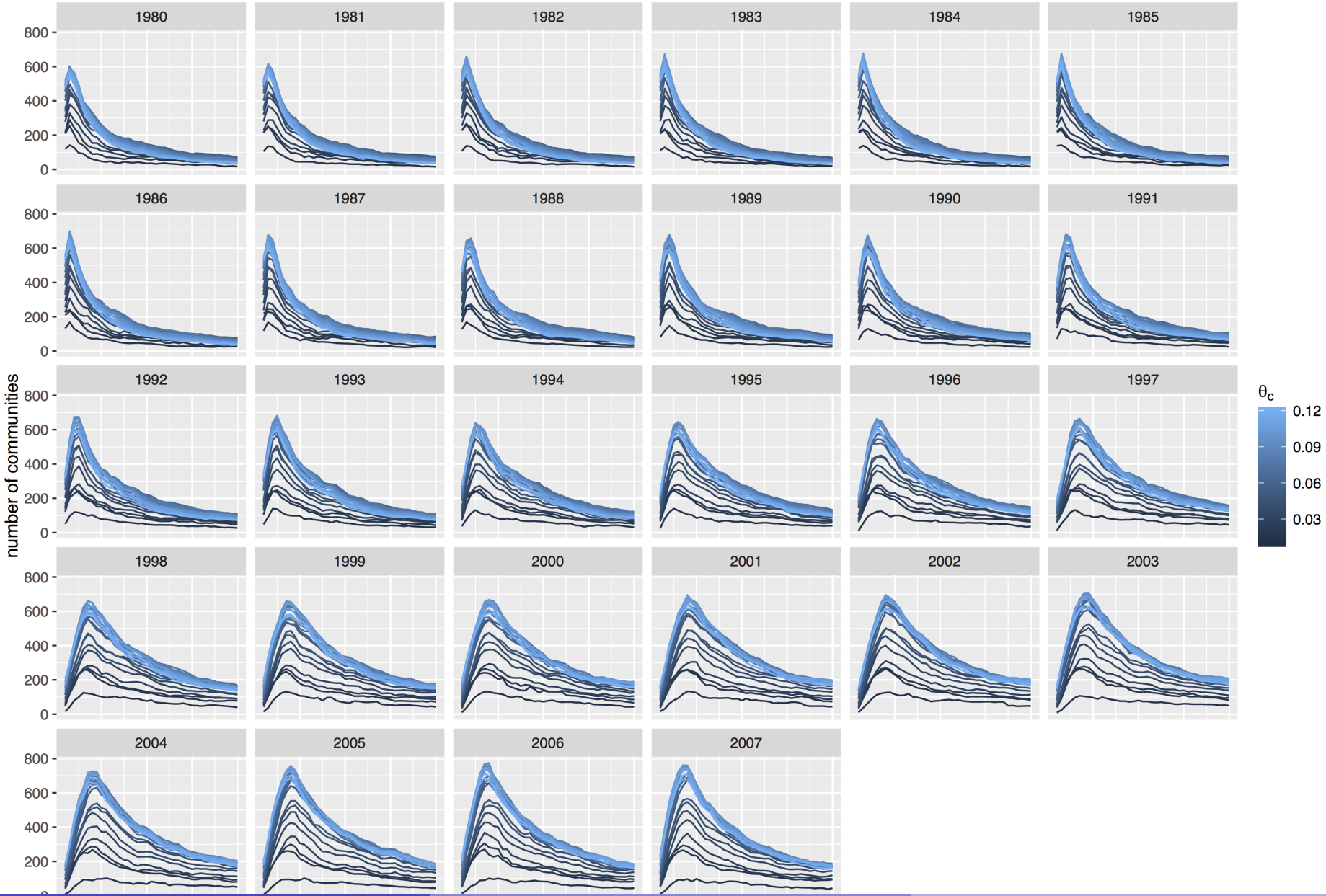
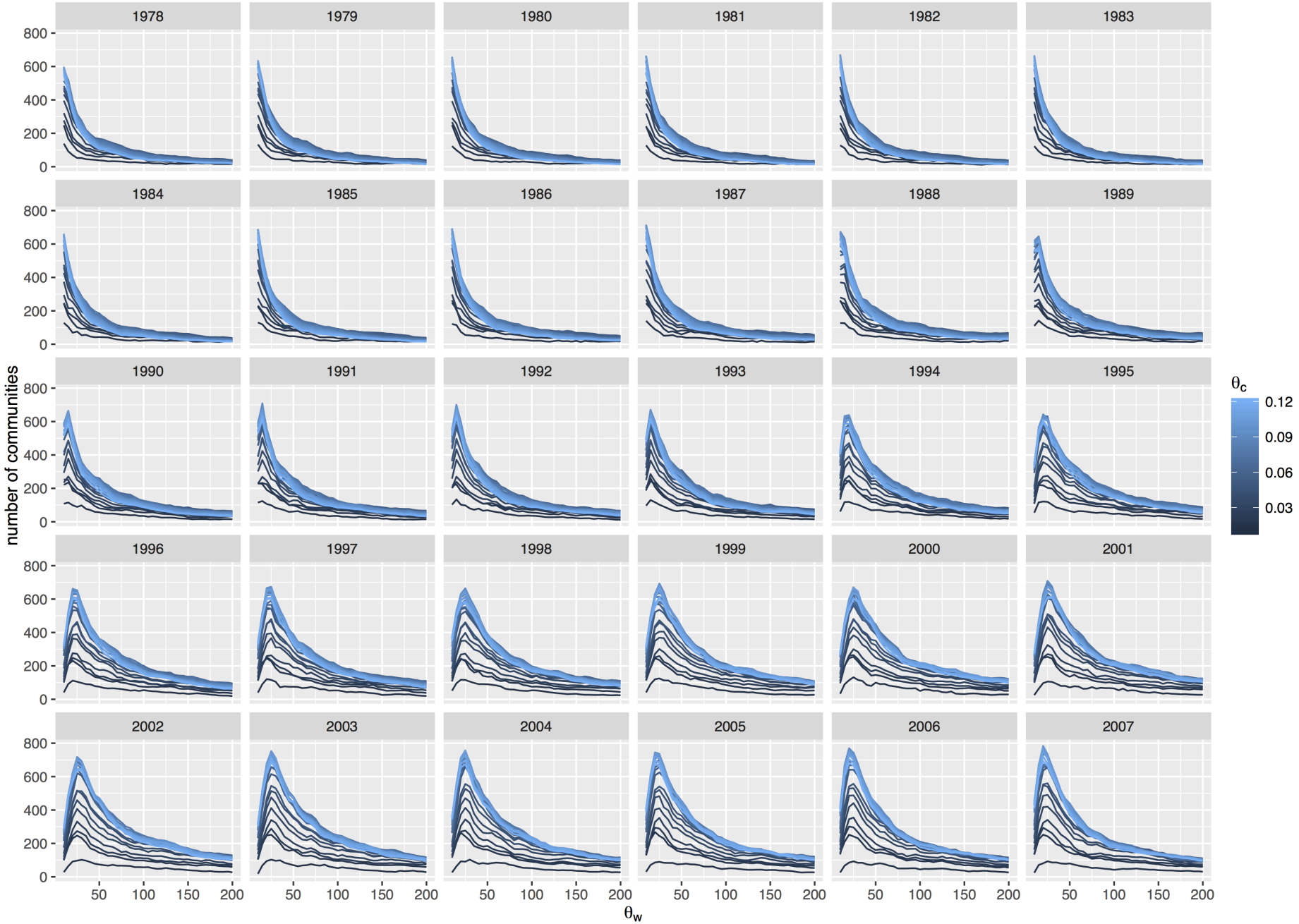


Network sensitivity analysis ($T_W = 2$)



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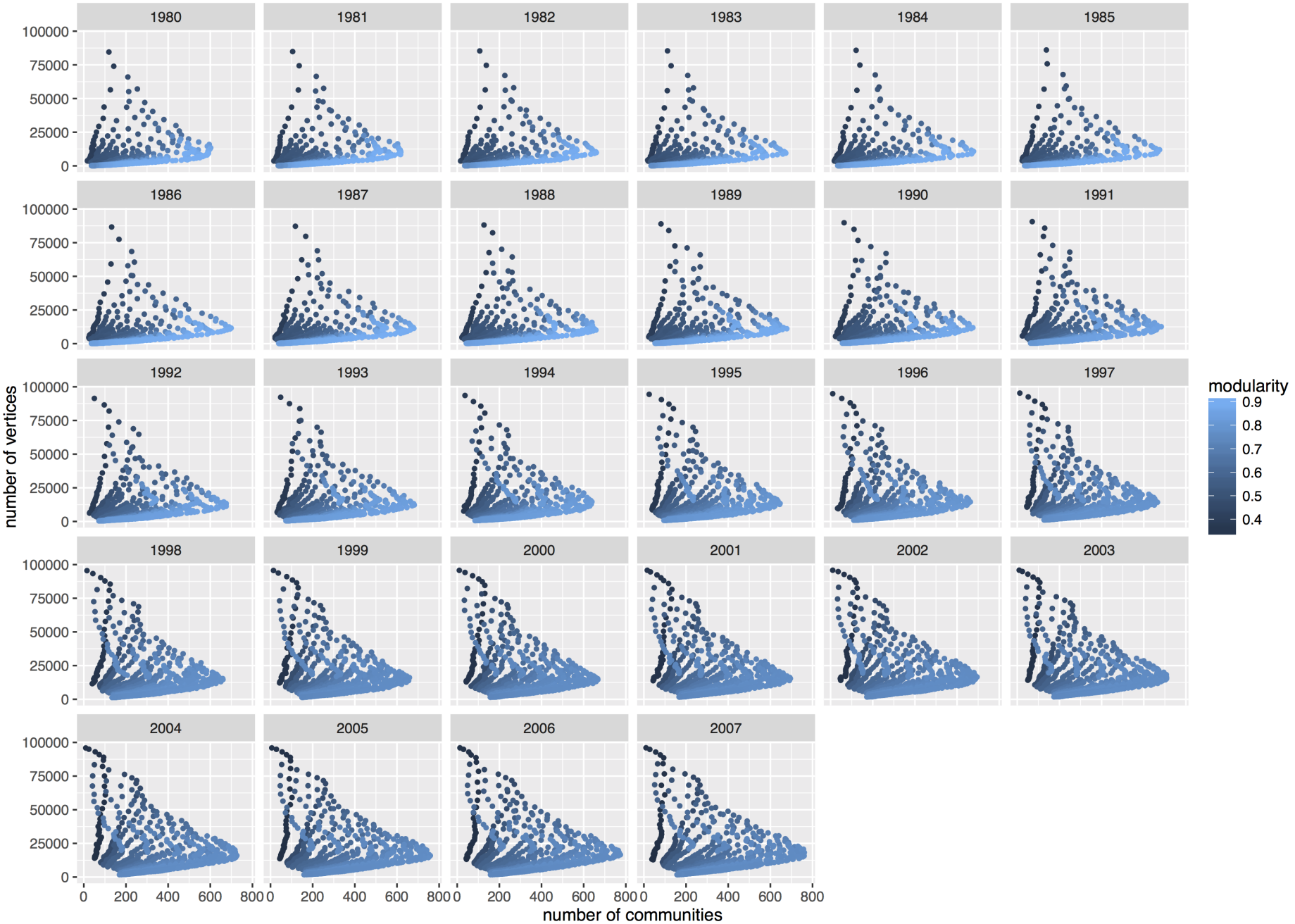

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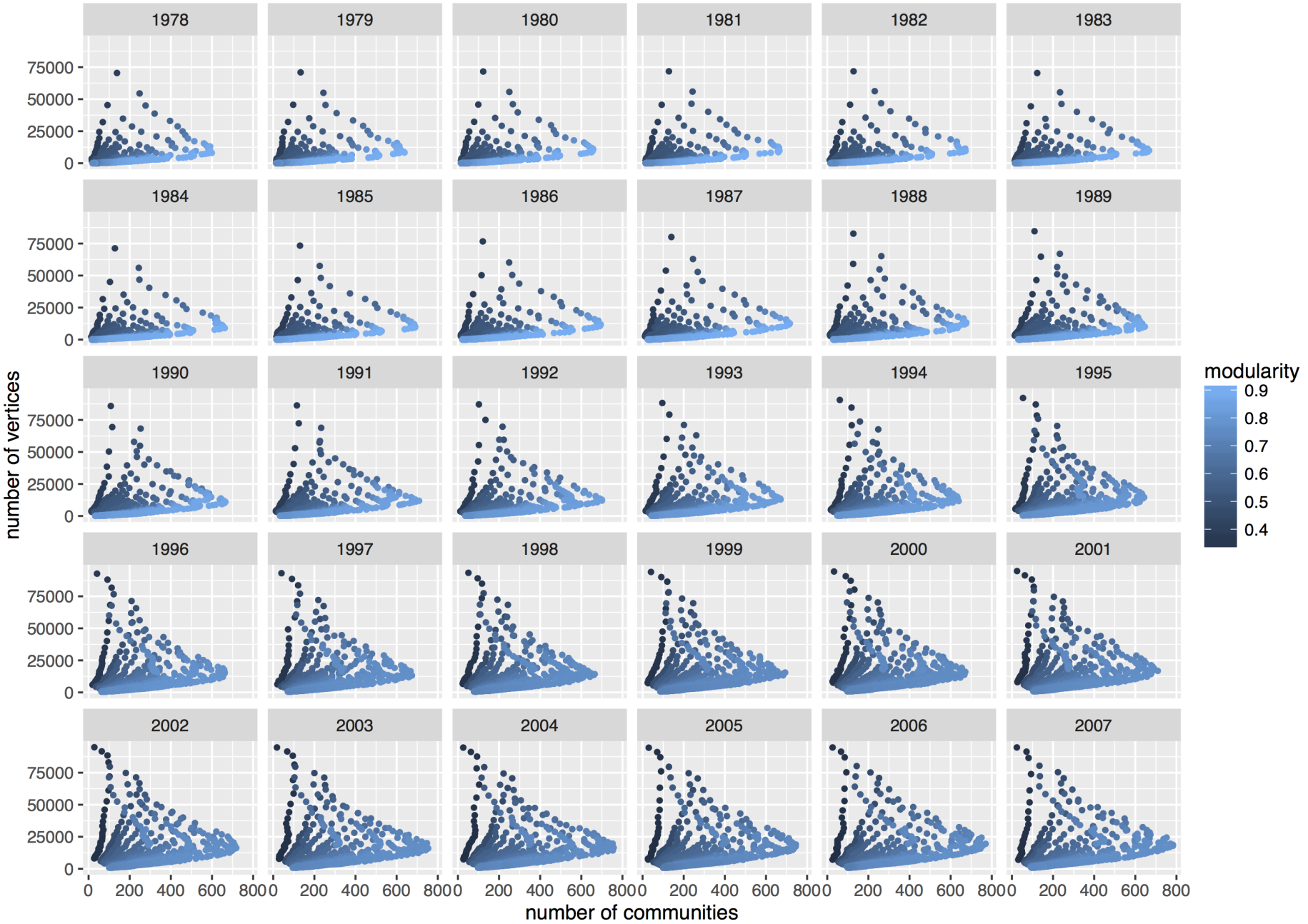
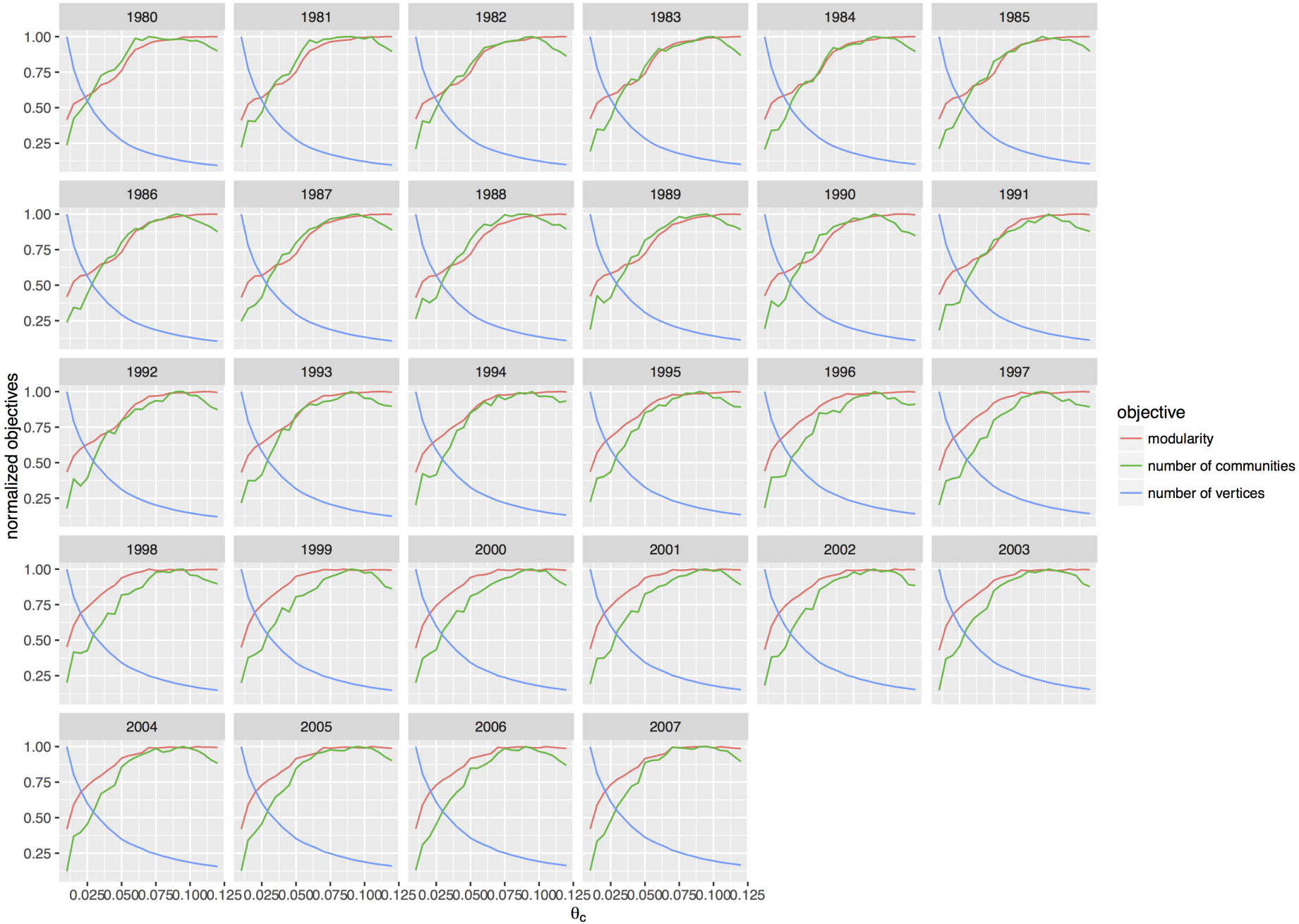
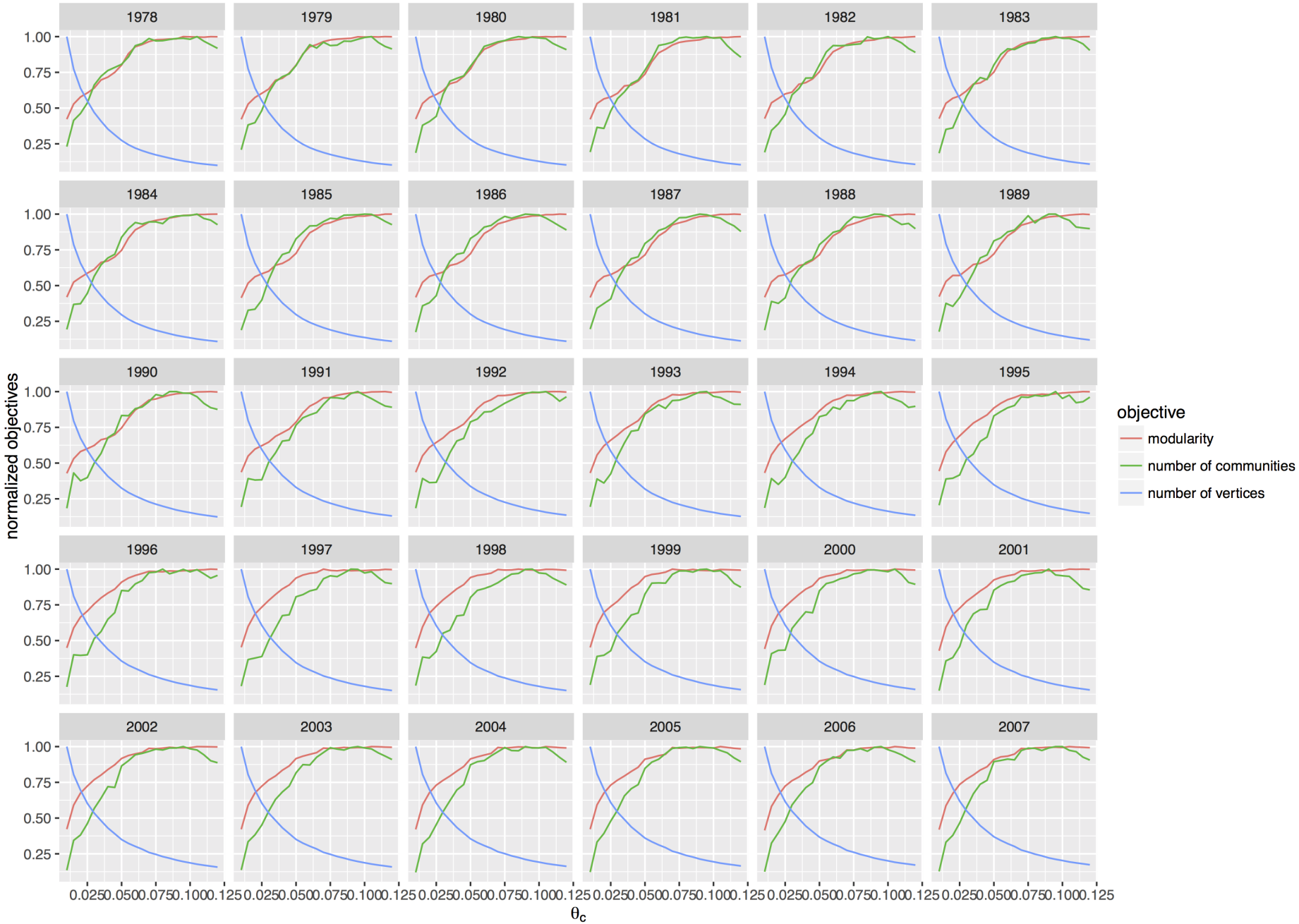


Network sensitivity analysis



Network sensitivity analysis ($T_W = 2$)



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