Can we read the impact of RDI policies in patent text? An application to wind technologies

A natural language processing model to evaluate the impact of RDI policies in the field of wind technologies

Antoine Lionel Reinhilde Simone

March 29, 2021

Overview

1. Introduction
2. Methods
3. Results
4. Conclusions/future work

Introduction

- There is a clear policy interest for green technologies in general and wind technologies in particular:
    - EU Green deal [COM(2019) 640]
    - EU Strategy on Offshore Renewable Energy [COM(2020) 741]
- Future technologies are key to ensure future production, since large efficiency gains are necessary in wind technologies and many technological challenges are ahead. In particular, a lot is expected from the private RDI spending [Pasimeni et al. 2019].
- To monitor public and private RDI investment and their effective output in wind technologies, the classical approach is to turn to patent data [JRC 2017] [Pasimeni et al. 2019] and find ways to identify the breakthrough technologies that constitute the essential elements of the knowledge base.

Methods

Name of the policy	Country	Approach	Time frame
US Wind Challenge	USA	Dedicated fund	1980-1999
PRC JV Wind	China	Lower regulation	1999-2003
Chinese Wind Fund	China	Fund for offshore tech	2010-2014
European Offshore Strategy	UE	Fund & Regulatory Framework	2020-
Danish Offshore Strategy	Denmark	Fund	1960-2020
German Wind Strategy	Germany	Fund	1999-

Table: Identification of major policies and funding programmes in the main countries.

Methods

Many different techniques have been used to assess qualitatively patents and how they interact with each other:

- Citations [Garfield 1955]
- Clusters of publications [Kajikawa et al. 2008]
- Network topology indicators [Iwami et al. 2014]
- Co-citations [Small 1973] [Boyack, Small, and Klavans 2013]
- Bibliographic coupling [Kessler 1963]
- NLP [Han 2017])

Methods

Our model recombines these well-abolished methods, an yields a NLP-powered network:

- Patents are linked by direct and indirect citations (at the patent family level)
- These links are weighted by the text similarity of the patents
- Clustering algorithms allow to identify sub-technologies which are composed of groups of similar patents

Methods

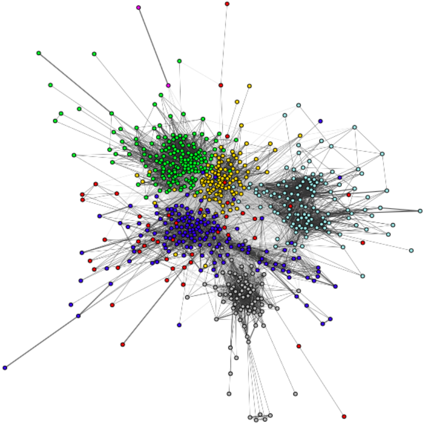

Figure: Patent network in wind tech

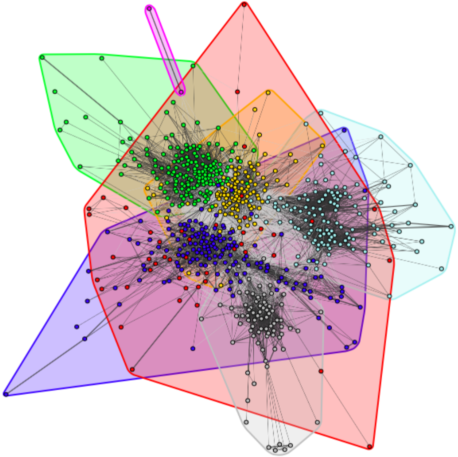

Figure: Identification of sub-technologies

Way forward

- Conduct a literature review on the evaluation of public policies in the wind sector, if possible using patents
- Make a table of public policies in the field of wind power in the main countries
- Identify the different important sub-technologies that the model shows in wind power
- Link the relevant companies with ORBIS (however it does not seem so easy at first glance, perhaps with the HAN identifier of the OECD)
- Filter the network by highlighting Chinese or Danish companies, the importance of universities, to seek network changes over time, or any other interesting focus.
- Indicators can be calculated for the points of the network concerned (centrality type in the network, are they bridges between the different technologies, etc.)
- Do wee see a policy impact on the centrality/betweeness of these patents over time?

Outstanding questions

Some technical yet crucial questions to be solved:

Patent quality

The quality filters that we discussed previously are good to identify highly cited patents, but maybe not in terms of quality of the content. For instance, many 'filtered' Chinese do not appear in the EP statistics, while we would expect highly important technologies to be protected in the EU and in the US.

Patent authorities and data availability

We have text data about EP patent only. US text data might be available in the internet as well, but that would require significant efforts to merge it with patents with the EPO. Is it possible to work the analysis on EP patents only without distorting too much the picture?

References I

- EU Commission, 'The European Green Deal' (Communication), COM(2019) 640 Final. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52019DC0640&from=EN
- EU Commission, 'An EU Strategy to Harness the Potential of Offshore Renewable Energy for a Climate Neutral Future' (Communication), COM(2020) 741 Final. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0741&from=EN
- Monitoring RI in Low-Carbon Energy Technologies, JRC105642 and Pasimeni F., Fiorini A., Georgakaki A. (2017) https://publications.jrc.ec.europa.eu/repository/bitstream/JRC105642/methodology_jrc_final_identifiers_pdf.pdf
- Pasimeni F., Fiorini A., Georgakaki A. (2019) Assessing private RD spending in Europe for climate change mitigation technologies via patent data, World Patent Information. https://setis.ec.europa.eu/publications/setis-research-innovation-data
- Garfield, Eugene. 1955. "Citation Indexes for Science." Science 122 (3159): 108–11.

References II

Kajikawa, Yuya, Junta Yoshikawa, Yoshiyuki Takeda, and Katsumori Matsushima. 2008. “Tracking Emerging Technologies in Energy Research: Toward a Roadmap for Sustainable Energy.” Technological Forecasting and Social Change 75 (6): 771–82.

Iwami, Shino, Junichiro Mori, Ichiro Sakata, and Yuya Kajikawa. 2014. “Detection Method of Emerging Leading Papers Using Time Transition.” Scientometrics 101 (2): 1515–33.

Small, Henry. 1973. “Co-Citation in the Scientific Literature: A New Measure of the Relationship Between Two Documents.” Journal of the American Society for Information Science 24 (4): 265–69.

Boyack, Kevin W, Henry Small, and Richard Klavans. 2013. “Improving the Accuracy of Co-Citation Clustering Using Full Text.” Journal of the American Society for Information Science and Technology 64 (9): 1759–67.

Kessler, Maxwell Mirton. 1963. “Bibliographic Coupling Between Scientific Papers.” American Documentation 14 (1): 10–25.

References III

Han, Qi, Florian Heimerl, Joan Codina-Filba, Steffen Lohmann, Leo Wanner, and Thomas Ertl. 2017. "Visual Patent Trend Analysis for Informed Decision Making in Technology Management." World Patent Information 49: 34–42.

Thank you!