

# AIML Powered Network Insights Expand the Identification of HCP Learning Relationships that can Boost Market Performance



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## INTRODUCTION

- Identifying, educating, and engaging local healthcare professional (HCP) thought leaders has remained a strategic imperative associated with launch excellence and the development of a successful product marketing strategy.
- Big multi-source healthcare databases, when combined with survey-based peer nomination data, support the effective use of AIML to accurately predict relationships between targeted HCPs and identified thought leaders across disease specific markets.
- Uncovering “hidden” local thought leaders and their HCP learning relationships at the clinical level creates powerful, new opportunities to promote new treatments and efficiently communicate their value.

## DATA PREPARATION

### Data Source

1. Primary HCP advice/discussion nomination data;
2. Prescription (Rx), Diagnosis (Dx), and Procedure (Px) data;
3. HCP demographic and affiliation data;
4. Sunshine act open pay data (general/research);
5. HCP publications/scientific leadership data.

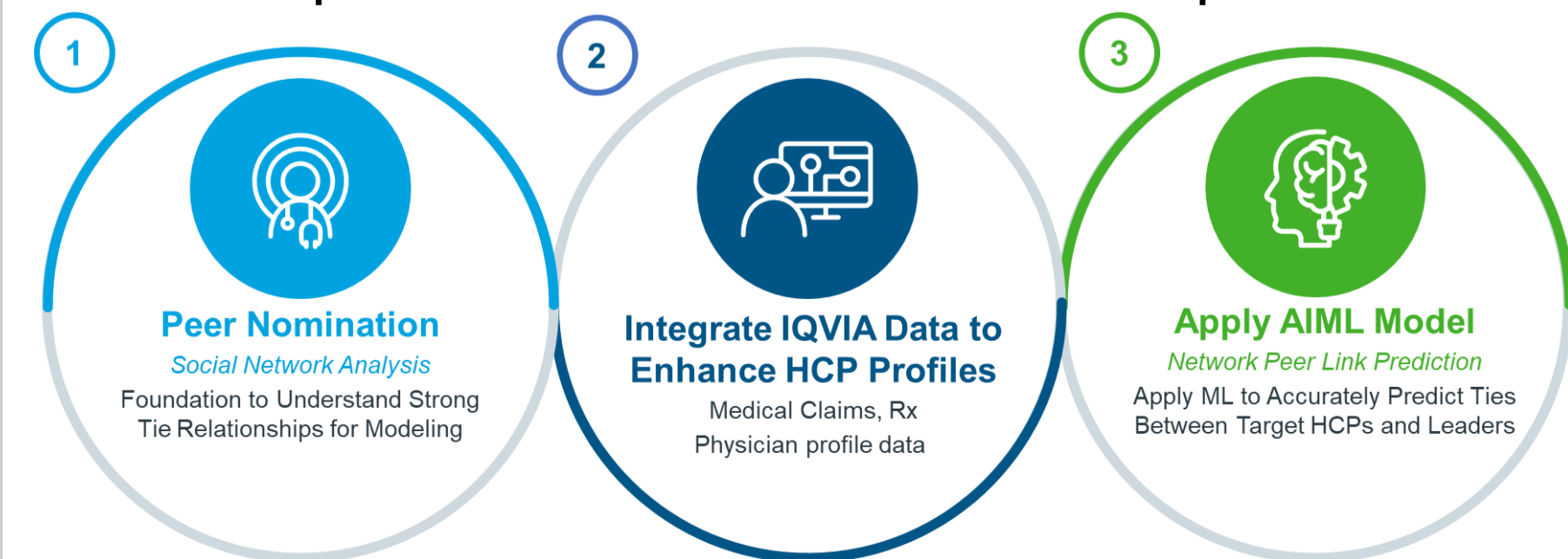


Fig 1. Data preparation for AIML modeling

## METHODS

- Our primary 'sociometric' survey-based research with targeted HCPs identifies peer networks based on learning, education, and collaboration connections with market thought leaders, which reveals peer relationship ties between targeted HCPs and those they nominate as trusted sources for learning and clinical guidance. Target HCPs are identified via client generated lists, proprietary market panels, and digital recruitment.
- We designed a novel framework (Figure 2) that leverages primary and secondary data sources to reveal hidden, clinically focused thought leaders and their peer networks at a disease specific market level.
- Our AIML predictive modeling (DNN, XGB, etc.) automatically prepares features from available data sets, learns and predicts leader/ follower relationships, and generates a highly accurate understanding of the full network of relationship ties that drive behavior and brand preference.

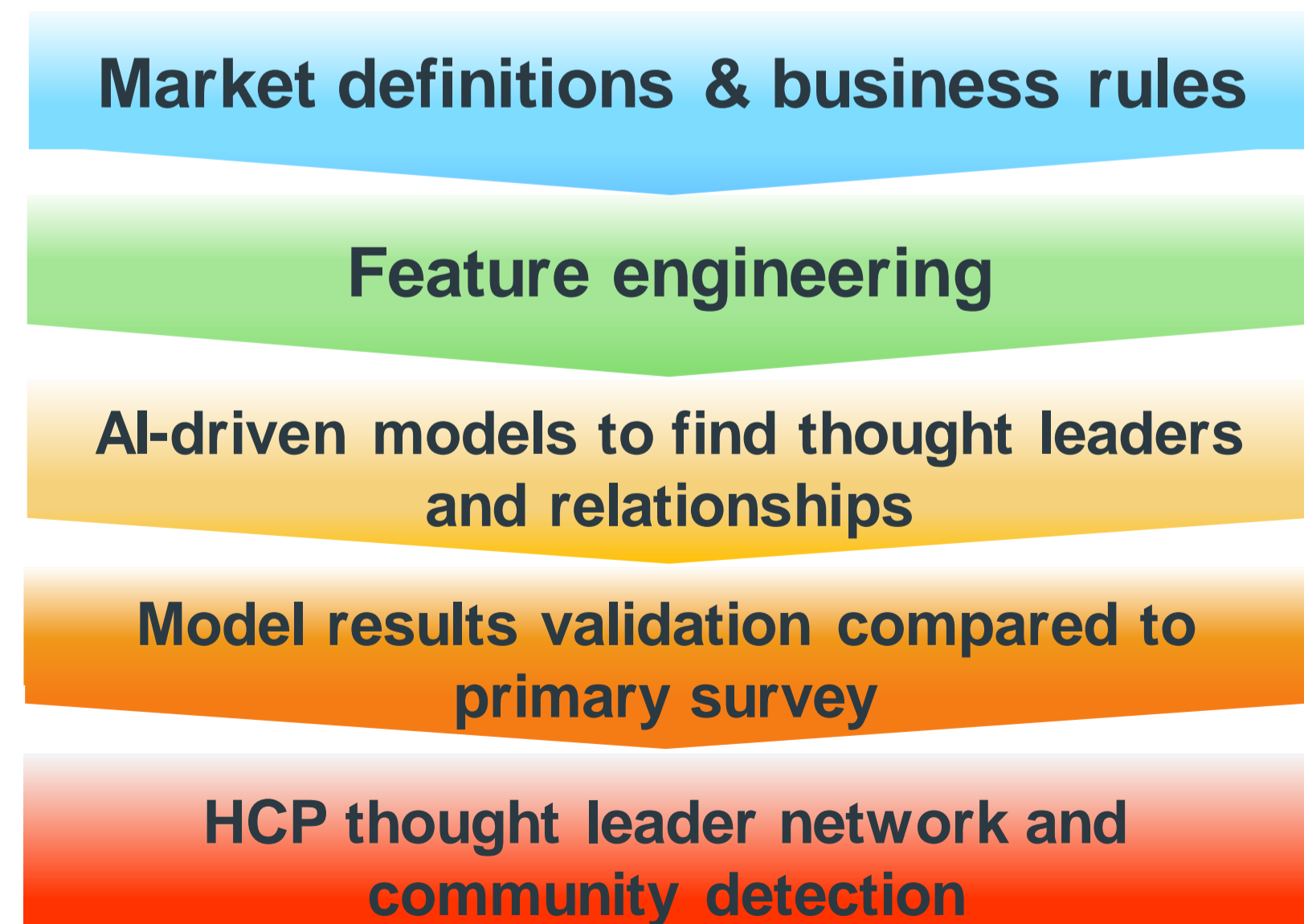


Fig 2. Flowchart of AI-driven HCP thought leader network generation framework

## EXPERIMENTS AND RESULTS

- We deployed our peer nomination prediction and HCP community detection framework to a real-world Multiple Myeloma (MM) market case study.
- Approximately 12K HCPs were identified in the US who are currently active in the treatment of MM patients.
- Primary peer nomination survey data from 855 respondents generated 1,125 nominations for MM clinical leaders and revealed 2,913 unique advice/discussion learning relationships.
- Our predictive model identified ~2.7K clinical MM leaders and expanded the identification of relationships from 2,913 (primary research) to ~42K (predictive modeling). Predictive precision was improved substantially from random guess from 0.11% to 45.4% (AIML models). With Louvain method, 98 local HCP communities were detected (Fig 3.) Figure 4 provides an example of the expanded insights generated from predictive modeling compared to primary research alone (187 leader/member relationship ties with primary research vs. 894 with predictive analytics).
- Shared patients, common affiliations and prescribing behaviors were found to be important features in driving model performance.

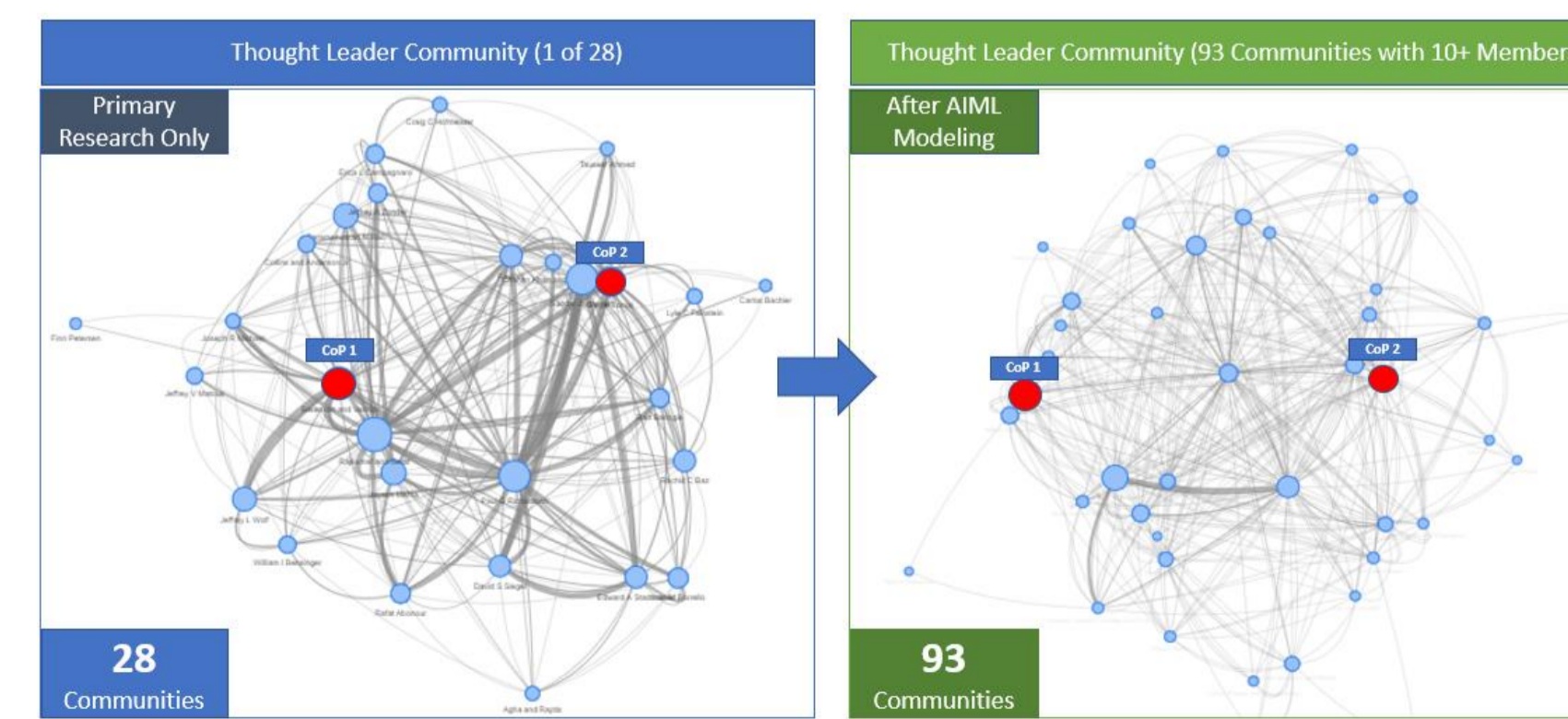


Fig 3. MM TL community expansion

## CONCLUSIONS

- Thought leaders are critical in validating new products and establishing the necessary credibility that leads to broader product adoption.
- Our real-world case study demonstrated the reliability of our predictive modeling solution for revealing the full scope of HCP thought leader relationships.
- These expanded insights can improve communication strategies that focus on “activating” these network relationships ties to achieve accelerated and improved market performance.

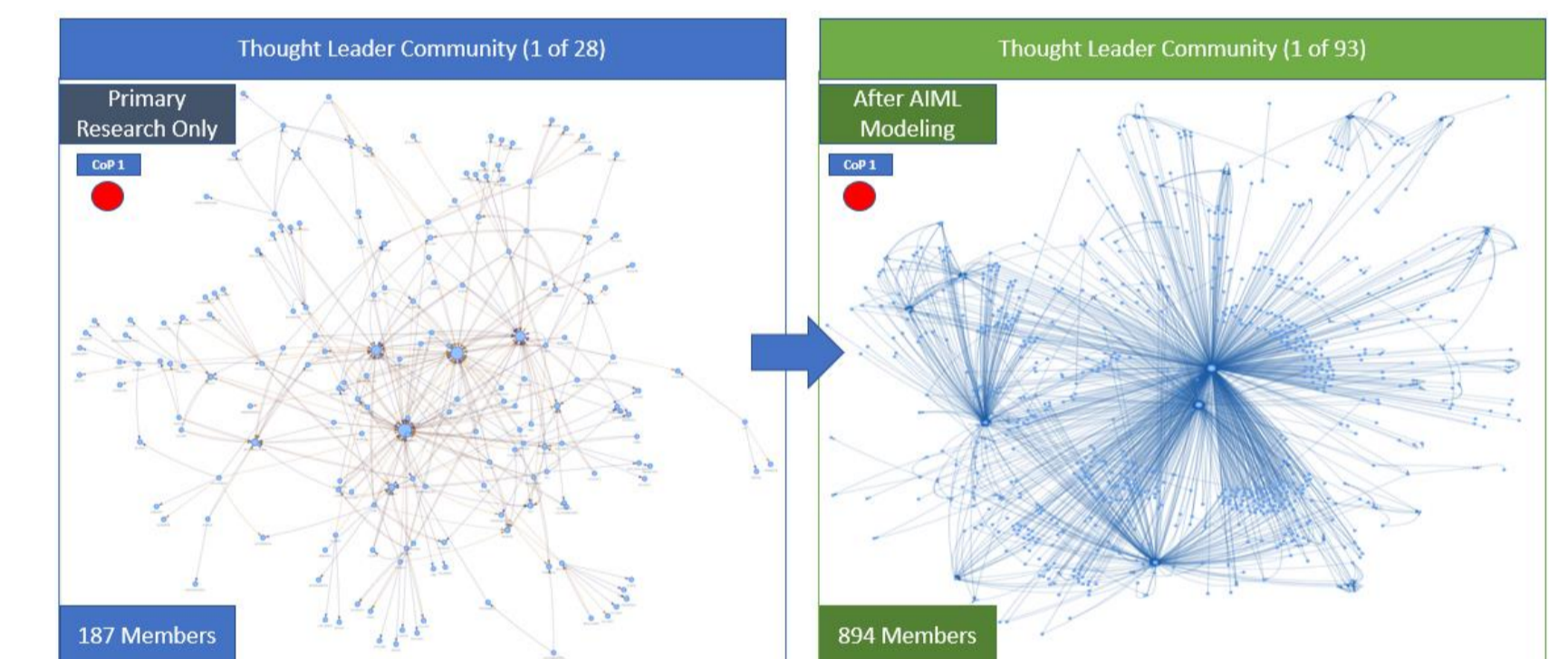


Fig 4. MM HCP market TL network expansion

## REFERENCES & ACKNOWLEDGEMENTS

- 1 Liu, Q., & Gupta, S. (2012). A Micro-level Diffusion Model for New Drug Adoption. *Journal of Product Innovation Management*, 29(3), 372-384.
- 2 Nair, H. S., Manchanda, P., & Bhatia, T. (2010). Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *Journal of Marketing Research*, 47(5), 883-895.