Formal Concept Analysis applied to Professional Social Networks

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Context and Motivation

- Online social networks for users oriented to business
- The LinkedIn is the one of the largest and most popular online professional social network
- The size and diversity of users generated content data
- The need to help professionals to increase skills and reach job positions
- The Formal Concept Analysis (FCA) as mathematical formulation for data analysis, applied to find patterns of professional competence

Goal

- Identify professional behaviors through data scraped from LinkedIn
- Find the minimum set of skills that is necessary to reach job positions
    - For example: statistic, machine learning, databases $\rightarrow$ data scientist
- Implications rules, specifically the set of proper implications

Contributions

- Our contributions are:
  - The domain problem mapping the model of competences
  - The professionals data set scraped from LinkedIn
  - The FCA-based approach
  - The set of experiments to apply FCA for professional career analysis

Formal Concept Analysis

- Based on the notions of concept and conceptual hierarchy
- A mathematical way to look at data and knowledge, their acquisition process and analysis based on lattices.
- There are three main principles:
  - Formal context
  - Formal concept
  - Implications

Formal Context

- Formal context (G, M, I)
  - a set G of objects
  - a set M of attributes
  - a binary relation $I \subseteq G \times M$

	a	b	c	d	e	f	g
18			x	x			
19		x				x	x
20	x	x		x	x		
21			x	x			x
22		x				x	
23	x	x		x	x		x
24			x	x			

Table: Example context of an user's *LinkedIn* skills.

Formal Concept

- Derivation operators:
  For $A \subseteq G$ and $B \subseteq M$

$$A' := \{m \in M | gIm \forall g \in A\}$$

$$B' := \{g \in G | gIm \forall m \in B\}$$

- Formal concept (A, B)

$$\begin{array}{cc} A \subseteq G & B \subseteq M \\ A' = B & B' = A \end{array}$$

  A is concept extent and B is concept intent

- e.g. formal concept $(\{18, 21, 24\}, \{$software engineering, data bases$\})$

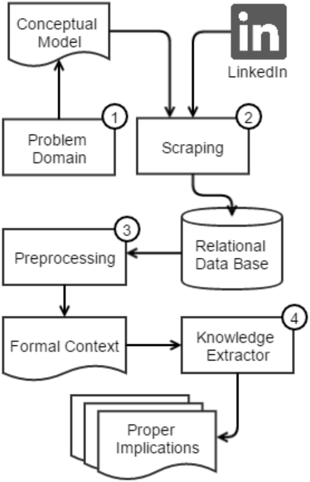
Implication Rules

- Being a formal context (G, M, I), an implication over M is $P \rightarrow Q$, where $P, Q \subseteq M$.
- P is the premise
- Q is the conclusion
- $P \rightarrow Q$ has to be such that $P' \subseteq Q'$, so the sets of attributes P and Q share the same subset of objects.

The Set of Proper Implications

- the right hand side of each implication is unitary: if $P \to m \in \mathscr{I}$, then $m \in M$;
- superfluous implications are not allowed: if $P \to m \in \mathscr{I}$, then $m \notin P$;
- specializations are not allowed, i.e. left hand sides are minimal: if $P \to m \in \mathscr{I}$, then there is not any $Q \to m \in \mathscr{I}$ such that $Q \subset P$.
- For example, $\{e\} \to \{a\}$ is a proper implication, but $\{e, g\} \to \{a\}$ is not a proper implication.

FCA-based Approach



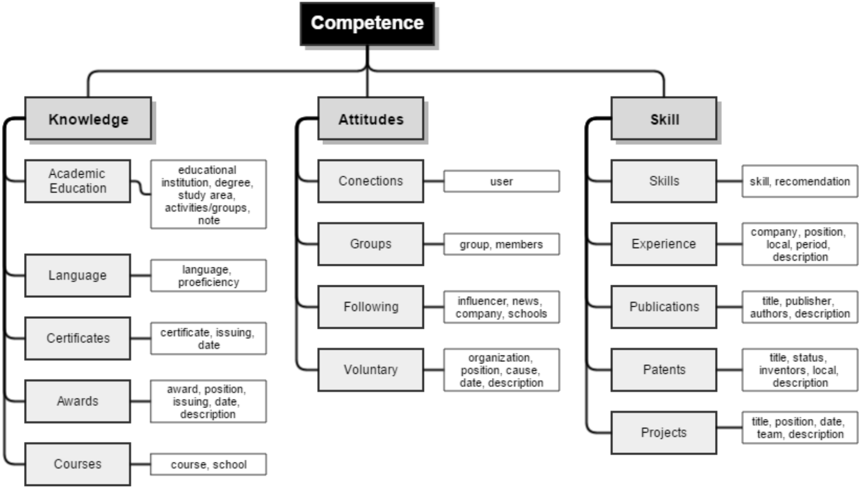
1 - Problem Domain

- Building the conceptual model according to the problem to be treated
- The classification of informational categories, based on Model of Competence

Figure: Duran(1998) adapted model

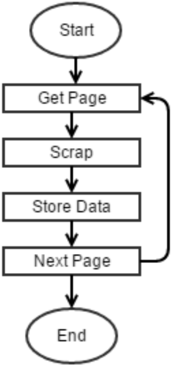
1 - Problem Domain

- We identified 3 dimensions, 14 aspects and 51 variables



2 - Scrapping

- The scrapping process was divided into two phases.
  - Selecting initial seeds randomly
  - Collecting the public profiles data: People undergraduate in IT coursers in Minas Gerais, Brazil



3 - Preprocessing

- We only considered the variables *skills* and *experience*
- The ETL process:
  - String cleaning: UTF-8 encoding correction, accent removal, standardization of all terms for the English language through Google Translate API
  - Attribute reductions: reductions based on semantic relevance

Generic term	Specific term
Java	JPA JSF
Software developer	Developer Programmer Program developer

  - Formal context with 366 attributes and 970 objects

4 - Knowledge Extractor

- The PropIm algorithm
  - Finding supersets: If $A \rightarrow b$, so $\uparrow |(A \rightarrow b)'|$ and $\downarrow |A|$
  - It computes proper implications with support > 0
  - Easily scalable strategy
  - Allows to set the attributes of interest for implications' conclusions
  - Problem complexity: $O(|M||\mathscr{I}|(|G||M| + |\mathscr{I}||M|))$
  - Pruning heuristic to reduce combinations possibilities among attributes

4 - Knowledge Extractor

Input : Formal context (G, M, I)
Output: Set of proper implications $\mathscr{I}$ with support greater than 0

$\mathscr{I} = \emptyset$
foreach $m \in M$ **do**
  $P = m''$
  $size = 1$
  $Pa = \emptyset$
  while $size < |P|$ **do**
    $C = \binom{P}{size}$
    $P_C = getCandidate(C, Pa)$
    foreach $P1 \subset P_C$ **do**
      if $P1' \neq \emptyset$ *and* $P1' \subset m'$ **then**
        $Pa = Pa \cup \{P1\}$
        $\mathscr{I} = \mathscr{I} \cup \{P1 \rightarrow m\}$
      end
    end
    $size{+}{+}$
  end
end
return $\mathscr{I}$

Function *getCandidate* (C, Pa)
  $D = \emptyset$
  foreach $a \in A | A \subset Pa$ **do**
    foreach $B \subset C$ **do**
      if $a \notin B$ **then**
        $D = P_C \setminus B$
      end
    end
  end
  return D

Experiments

The goal was to answer the following questions:

- How do proper implications identify relations between skills and positions?
- Could we find intersections among sets of skills, and what do these intersections represent?

Proper Implications to Competence Identification

- We selected 20 positions and their 180 skills
- It was extracted 895 proper implications with PropIm algorithm

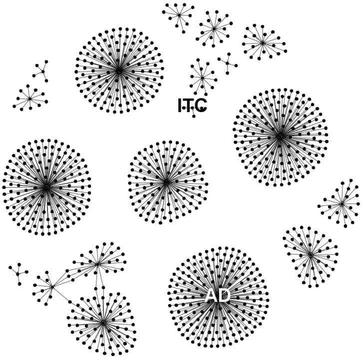


Figure: Proper implications network. AD = *Administrative Director*, ITC = *IT Consultant*

Proper Implications to Competence Identification

- Nodes with high in-degree value represent positions which have more diversification of sets of skills
- 163 proper implications
- $\{$*entrepreneurship, human resources, information management*$\} \rightarrow \{$*administrative director*$\}$

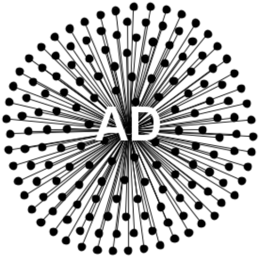


Figure: AD = *Administrative Director*

Proper Implications to Competence Identification

- Nodes with low in-degree value represent jobs positions that demand more specific sets of skills
- 3 proper implications
- $\{ABAP, agile\ methodology, BI\} \rightarrow \{it\ consultant\}$

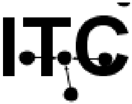


Figure: ITC = *IT Consultant*

Intersection Between Skills and Job Positions

- Top 3 best jobs in Information Technology area according to *Career Cast research* (Cast, 2016)
- Edges weight = relative frequency $\mathscr{F} = \dfrac{F_i}{F_p}$, where $\mathscr{F}$ is the relative frequency, F_i is the implication absolute frequency and F_p is $|m'|$
- Why relative frequency?
  $\{$java frameworks$\} \rightarrow \{$software engineer$\}$
  Support: 2.47%
  Relative frequency: 75.56%

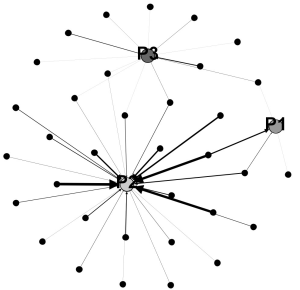


Figure: P_1: *data scientist*, P_2: *information security analyst* and P_3: *software engineer* job position

Intersection Between Skills and Job Positions

- Nodes P_1 and P_2 share two set of skills:
  - $\{$*agile methodology*$\} \rightarrow \{$*data scientist*$\}$
  - $\{$*agile methodology*$\} \rightarrow \{$*information security analyst*$\}$

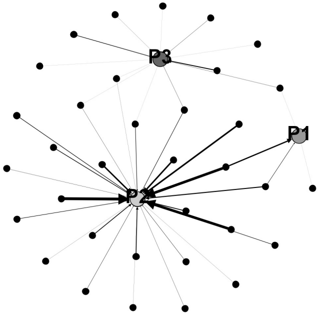


Figure: P_1: *data scientist*, P_2: *information security analyst* and P_3: *software engineer* job position

Intersection Between Skills and Job Positions

- Skills and positions related to hierarchical transition:
  - P_1: $\{$*.NET, automation systems*$\} \rightarrow$ *IT analyst*
  - P_2: $\{$*.NET, data base, ERP, it governance*$\} \rightarrow$ *IT coordinator*
  - P_3: $\{$*BPM, cloud computing, CRM*$\} \rightarrow$ *IT manager*
  - P_4: $\{$*assets management, BI, business management, consulting*$\} \rightarrow$ *IT director*

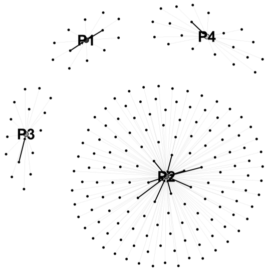


Figure: P_1 to P_4 represents the following job positions: P_1 is *IT analyst*, P_2 is *IT manager*, P_3 is *IT coordinator* and P_4 is *IT director*

Conclusions

- FCA-based approach to identify the minimum sets of skills that is necessary to achieve a job position
- Set of experiments for apply FCA to professional competences analysis
- Computational strategy to find proper implications without loss of information
- In-degree of conclusions nodes mean the diversification among sets of skills for the same job position
- Sharing sets of skills do not determine the job position, but show positions that can be achieved
- The disjointed sets (representing hierarchy) show that is necessary develop skills of different natures to progress in career

Future Works

- Experiments will be replicated for other areas
- Exploring another algorithms which extract implications from concept lattice, or from the set of formal concepts
- Expanding the analysis to all dimensions from *model of competence*
- Implementing an web environment with this FCA-based approach, for help professionals to increase skills and look for possible job positions
- Preprocessing: attribute fusion through correlation analysis
- Temporal analysis of career evolution
- Estimate the remuneration of people based on posts and professional data

Any questions?

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