Transfer Learning for Depression Detection on Social Networks*

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Abstract. The abstract should briefly summarize the contents of the paper in 150–250 words.

Keywords: psychological knowledge base · supervised learning · depression.

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1 Introduction

2 Related Work

3 Definitions/Research Problem

.... The research objective is defined:
Definition 1 *Let $\mathbb{S}$ be a set of user properties to present an effective user profile for depression, a user property $s \in \mathbb{S}$ is a tuple $s := \langle\ p_1,\ p_2,\ p_3,\ \cdots\ p_n\ \rangle$, where*

- *p is a visualisation or instance of an user property;*
- *p is not a mental or depression close-related symptom;*
- *n could be an infinite integer so the number of p elements could be unlimited;*
- *all p elements in the same user profile are generally independent.*

With clear definition of research objective, the research target is defined:
Definition 2 *Let $\mathbb{V}$ be a set of labeled user depression, a label of user depression $v \in \mathbb{V}$ is a screening result of personal depression, where*

- *when v is binary, it presents depression (1) or healthy (0);*
- *when v is scale, it presents the severity of depression from healthy (0) to most severe depression(1).*

From Definition 1, any given user property s $\in \mathbb{S}$ is possibly overlapped with other user properties. The overlapped information in user profile apparently doesn't suit for classification. While learning from related psychological researches, a set of user personal functionings can present a perfect reflection of user mental profile. It innovates a creative method that detecting user depression by analysis of a set of user functionings. Therefore, the research problem is defined:
Definition 3 *Let $\mathbb{U} = \langle\ u_1,\ u_2,\ u_3,\ \cdots\ u_k\ \rangle$ be a subset of $\mathbb{S}$, any element $u \in \mathbb{U}$ is a tuple $u := \langle\ p'_1,\ p'_2,\ p'_3,\ \cdots\ p'_{n'}\ \rangle$,where*

- *$\mathbb{U}$ is a machine-learning descriptive subset transferred from $\mathbb{S}$ in psychological domain descriptive;*
- *every $p' \in u$ is assigned from a instance $p \in s$ in Definition 1;*
- *$|\mathbb{D}^s|$ is limited due to the limited functionings defined in psychological domain.*

This research aims to discover an effective classification model $\mathbb{M}$ which provides a reliable mapping of a well-defined $\mathbb{U}$ into $\mathbb{V}$:

$$\mathbb{U} \xRightarrow{\mathbb{M}} \mathbb{V} \text{ or } \mathbb{M}(\mathbb{U}) = \mathbb{V}$$

4 Conceptual Framework

Therefore, the research problem is decomposed into two tasks:

1. data processing;
2. modelling.

4.1 Conceptual Design

Driven by the processing of tasks, the conceptual framework of the proposed approach is designed consisting of three modules, as illustrated in Fig. 1.

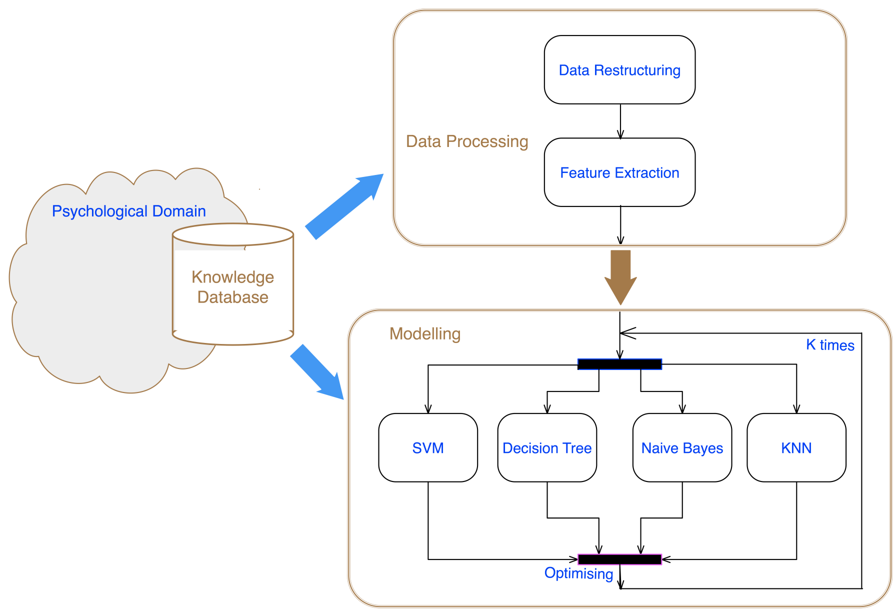

Fig. 1. Conceptual Framework

4.2 Psychological Knowledge Base

Psychological Domain Knowledge Kroenke et, al. [102] concluded that there was a strong association between increasing depression severity screen scores and worsening functionality on all 6 function: mental, social, role, pain, physical and overall functions. Other psychological researchers [103][104][105] also delivered similar opinion on the relation between depression and functions.

Transfer Domain We hence can transfer psychological domain knowledge to information domain. $|\mathbb{D}^s|$ can be narrowed down to 6. The dataset of user mental profile is redefined:

Definition 4 *Let new redesigned* $\mathbb{U} = \langle\, u_{mental},\, u_{social},\, u_{role},\, u_{pain},\, u_{physical},\, u_{overall} \,\rangle$, *every* $u \in \mathbb{U}$ *is an independent function of user, where*

- u_{mental} *presents mental function;*
- u_{social} *presents social function;*
- u_{role} *presents role function;*
- u_{pain} *presents pain function;*
- $u_{physical}$ *presents physical function;*
- $u_{overall}$ *presents the overall function.*

4.3 Data Processing

(see Fig. 2).

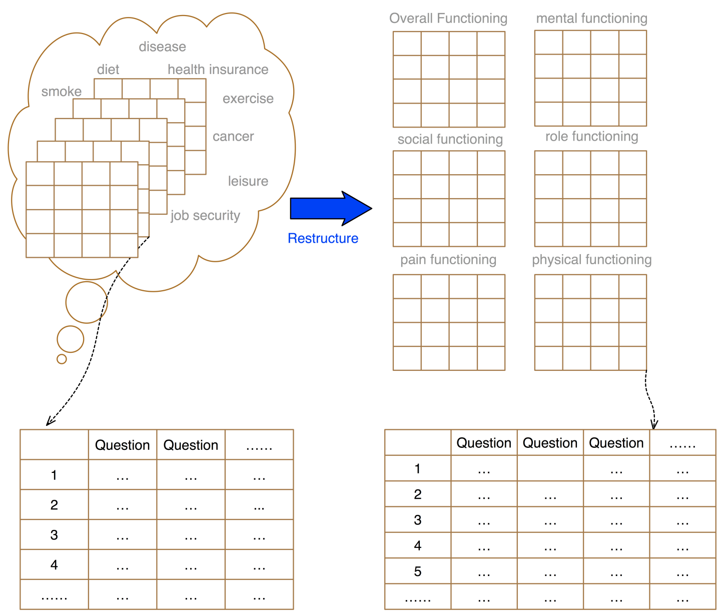

Fig. 2. Data Restructure based on Psychological Knowledge Base

4.4 Modelling

Given a health dataset $i = \langle\, \mathrm{u}_{mental},\, \mathrm{u}_{social},\, \mathrm{u}_{role},\, \mathrm{u}_{pain},\, \mathrm{u}_{physical},\, \mathrm{u}_{overall} \,\rangle$,

input : $i = \langle\, \mathrm{u_{mental}}, \mathrm{u_{social}}, \mathrm{u_{role}}, \mathrm{u_{pain}}, \mathrm{u_{physical}}, \mathrm{u_{overall}} \,\rangle$
output: ensemble modol

special treatment of the first line;
foreach *element e of the line i* **do** `FindCompress`(p);

Algorithm 1: Ensemble

5 Experiment

5.1 Experiment Design

5.2 Baseline Models

5.3 Performance Measuring Methods

6 Results and Discussions

6.1 Experimental Results

6.2 Discussions

7 Conclusion and Future Work

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