Mental Health: Exploring Neural Networks To Study Stress In The Tech Industry

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INTRODUCTION

Work and love are two major domains of our lives from which most people get satisfaction and find meaning; at the same time these can act as life-threatening stressors. Rapid economic change is one of the most significant aspects of our times. Behind the curtain of world economy globalization, the occupational environment is delivering increasing stress, such as job insecurity, increasing workload, and the burden of lifelong learning. Larger proportion of employees became involved in service- and knowledge-based industries requiring heavy technological preparedness and mental stress. If the pace of change exceeds the capacity of the workers to cope, negative stress reactions can occur. Negative stress reactions are not limited to the individual worker, but also may affect the worker's family, and the community in which they live.

Workplace can function as a secure base for promoting mental health since many workers spend more awake time at work than at home. But the stigma attached to having a psychiatric disorder is such that employees may be reluctant to seek treatment. It is desirable to focus on how to get rid of any potential risk rather than who is most responsible for it.

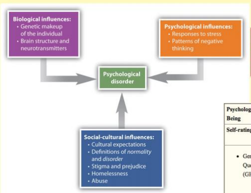


Figure 1: The Bio-Psycho-Social Model. The bio-psycho-social model of disorder proposes that disorders are caused by biological, psychological, and social-cultural factors.

Psychological Well-Being	Symptoms	Disorder
Self-rating scale	Self-rating scale	Clinical diagnosis with/without structured interview
• General Health Questionnaire (GHQ)	• The Center for Epidemiological Studies-Depression (CES-D) • Beck Depression Inventory (BDI) • Hamilton Rating Scale for Depression (HAM-D) • The Profile of Mood States (POMS) • Zung Self-Rating Depression Scale (ZDS)	• Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) • National Institute of Mental Health Diagnostic Interview Schedule (DIS) • Structured Clinical Interview for DSM Disorders (SCID) • The World Health Organization's Composite International Diagnostic Interview (CIDI)

Because there are no clear biological diagnoses, psychological disorders are difficult to diagnose. Currently, it is on the basis of emotional states and clinical observations of the behaviors that the individual engages in.

Figure 2: Diagnostic Methods for Three Levels of Conditions Related with Mood Disorder

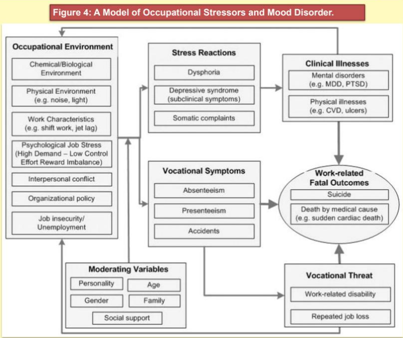
PROBLEM STATEMENT

As shown below, there are many signs indicative of stress in a person. In this project, the focus is on mood swings. Using Recurrent Neural Networks we can identify how frequently the sentiment of a person changed over a span of time. This can be an indicator of an underlying health condition like stress. It can also be an indicator of a more serious condition like "mixed state" where a person may experience symptoms of both manic and depressive state over the course of a few minutes.

Figure 3: It is sometimes easier for someone else to recognize stress in you but not so easy to recognize it yourself

Psychological Signs	Emotional Signs	Physical Signs	Behavioral Signs
Inability to concentrate or make simple decisions Memory lapses Becoming rather vague Easily distracted Less intuitive & creative Worrying Negative thinking Depression & anxiety	Tearful Irritable **Mood swings** Extra sensitive to criticism Defensive Feeling out of control Lack of motivation Angry Frustrated Lack of confidence Lack of self-esteem	Aches/pains & muscle tension/grinding teeth Frequent colds/infections Allergies/rashes/skin irritations Constipation/diarrhoea/IBS Weight loss or gain Indigestion/heartburn/ulcers Hyperventilating/lump in the throat/pins & needles Dizziness/palpitations Panic attacks/nausea Physical tiredness Menstrual changes/loss of libido/sexual problems Heart problems/high blood pressure	No time for relaxation or pleasurable activities Prone to accidents, forgetfulness Increased reliance on alcohol, smoking, caffeine, recreational or illegal drugs Becoming a workaholic Poor time management and/or poor standards of work Absenteeism Self neglect/change in appearance Social withdrawal Relationship problems Insomnia or waking tired Reckless Aggressive/anger outbursts Nervous Uncharacteristically lying

Figure 4: A Model of Occupational Stressors and Mood Disorder.



DATA

1. Dataset:
   X_train,Y_train (127 sentences for training)
   Y_train is integer label between 0 and 4 corresponding to an emotion for each sentence X_train
   X_test, Y_test (56 sentences for testing)
   30 minute audio recording "A" of tech worker speaking at work
   Audio->Text conversion "A"->"P". "P" is paragraph of sentences
   Split "P" into sentences "S". This is input to Neural Network.

2. Pre-trained word embeddings for dictionary of 400,001 words is used.

3. First the training sentences are converted into lists of indices, zero-padded so that their length is the length of the longest sentence. This is to ensure all the mini-batches are of the same length.

5. The pre-trained Embedding layer using the embedding matrix is defined and made non-trainable.

6. Output of Embedding layer is connected to LSTM network which takes word sequences as input.

7. LSTM model takes word ordering into account and predicts the most appropriate emotion conveyed by the sentence.

8. Keras is used to compile the model, define the categorical_crossentropy loss, Adam optimizer and accuracy metrics.

MODEL

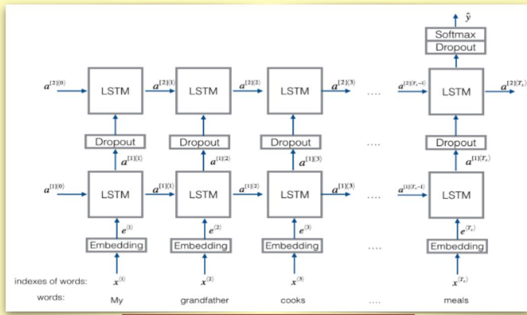


Figure 6: A Keras graph of the 2-layer LSTM sequence classifier

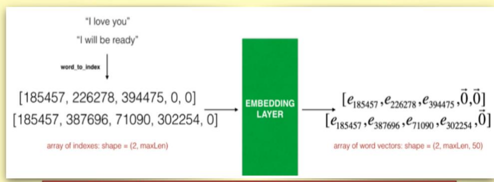


Figure 7: This example shows the propagation of two examples through the embedding layer. Both have been zero-padded to a length of `max_len=5`. The final dimension of the representation is `(2,max_len,50)` because the word embeddings we are using are 50 dimensional.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 10)                0
_________________________________________________________________
embedding_2 (Embedding)      (None, 10, 50)            20000050
_________________________________________________________________
lstm_2 (LSTM)                (None, 128)               91648
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 645
_________________________________________________________________
activation_1 (Activation)    (None, 5)                 0
=================================================================
Total params: 20,092,343
Trainable params: 92,293
Non-trainable params: 20,000,050
_________________________________________________________________
```

Figure 8: Model summary as seen in Keras. Since the vocabulary size has 400,001 words (with valid indices from 0 to 400,000) there are 400,001*50 = 20,000,050 non-trainable parameters.

RESULTS

1. Model is trained to take as input an array of shape (m, max_len) and output probability vectors of shape (m, number of classes). So X_train (array of sentences as strings) is converted to X_train_indices (array of sentences as list of word indices), and Y_train (labels as indices) to Y_train_oh (labels as one-hot vectors).

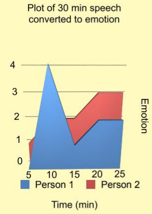
2. Epochs 50, Batch size = 32

3. Test Accuracy using (X_test, Y_test) of 56 sentences: > 90%

4. Now the model is used to interpret "S". Output of predicted emotions and changes is plotted accurately.

5. Further experiments with tuning the model are detailed in the project report.

CONCLUSION



The labels used in this experiment are as follows:
0 - Heart, 1 - Sport/Other, 2 - Happy, 3 - Unhappy, 4 - Hungry

By extending the training set and pre-trained word matrix to include a larger set, it is possible to capture most of the speech words.

FUTURE WORK

The challenge for most companies is that stress relief programs are purely voluntary and left to the individual's choice to avail them. It is very difficult for an individual to predict their tolerance level and seek timely assistance. This is where AI can help.

If we can think of unique ways to bridge this gap using AI and Deep Learning, it would make a significant and impactful difference to everyone.

Based on my analysis, listed in below table (Figure 5) are some markers that I feel can be used as good indicators to monitor the stress level of tech workers. In this project, I have used "1.Mood and emotional disposition" as an example.

Similarly, by studying the other indicators, we can represent the findings per person in a format. Example: 100 X 100 X Time parameters card similar to image pixels.

Using these "cards" as input to deep learning, we should be able to identify novel ways to:
A. Represent the stress level of a tech worker on a scale (such as 1 through 10)
B. Predict the tipping point based on duration for which a tech worker has been exposed to various degrees of stress.
C. Approximate the life expectancy or health risks associated with each stress level.
D. Predict when to take prevention measures to help avoid burnout.
E. Predict the recovery period from a burnout condition given certain measures were taken.

The derived analysis can be used in various ethical ways to improve the quality of life for everyone.

Figure 5

Unique indicators for a person	Unique indicators in an office area/team	Special scenarios
1. **Mood and emotional disposition** 2. Confidence and general personality disposition 3. Posture, gait, weight and physical disposition 4. Time spent in sunlight per day 5. Time spent in fresh air per day 6. Travel time, frequency of travel and jet lag 7. Holidays availed for relaxation 8. Speech/Lack of speech 9. Eyes strain and screen time 10. Keyboard typing style 11. Work hours onsite and remote 12. Tobacco/Alcohol/Substance consumption 13. Caffeine consumption 14. Water consumption 15. Food habits 16. Exercise 17. Driving patterns 18. Sleep patterns 19. Alternately abled 20. History of life events	1. Indoor lighting condition 2. Indoor air quality 3. Ergonomic conditions 4. Measure laughter in teams. How often teams laugh together can be measured using deep learning (reference link 11) 5. Team dynamics and energy 6. Work environment and quiet spaces to think, work, rest	1. Recent life events 2. Social/Economic/Political climate

RELATED WORK AND REFERENCES

There is some ongoing research in the area of using artificial intelligence for mental health. But given the vastness and the difficulty of the problem, there is room for more research and breakthroughs.

Although I could not find targeted work for the specific use case of the tech worker population, some of the references below are related and complement the cause.

MIT researchers [2018] detail a 'context-free,' neural-network model that can be unleashed on raw text and audio data from patient interviews to discover speech patterns indicative of depression.

In [Balakrishnan, Rege, 2017], a system that can detect 8 major dimensions and basic emotions from speech has been explained. It was created using the SEMAINE dataset. Further, the paper explains related techniques.

[Osmani etall 2015] talks about an experiment to use smartphones to track the progress of patients with bipolar disorder in Austria.

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