

Abstract

Abstract: 911 is often the first place contacted for dealing with behavioral health related (BHR) issues. Its estimated at least a fifth of all calls are related to behavioral health, and with BHR affected convicts having a recidivism rate of around 30%, its not hard to see how straining these issues can become on systems already stretched thin, where chronic understaffing is often a reality. A great solution would be if we could intervene as soon as possible to get people the treatment they need, police reports would be excellent for identifying and treating these individuals, but annotation is a long tedious task only certain people have security clearance to do and as mentioned earlier departments are often understaffed. That is why with the help of keywords given to us by behavioral health professionals, we have developed a model for automatic categorization of police reports that can classify police reports into several categories of class type (Situation, Situation Mental Health, Child, Disposition, Disposition Mental Health, Drugs, Medication, Medication Mental Health) by learning the correlation between co-occurrences of class types given keywords, evidence type given keywords, and class type given keywords and then combining those with the embeddings of a Feed Forward Network that analyzed relevant sentences from reports. With this model we were able to achieve an accuracy rate of 72% which was significantly higher than other state of the art methods typically used.

Introduction

Around 60 million Americans suffer from mental health issues [1], and nearly 46.3 million suffer from substance use disorders [2]. For these individuals first responders like EMTs, police, and fire are often the first contacted. Overall, at least 20% of 911 calls involve behavioral health, at the end of the month first responders typically annotate these Behavioral Health Related (BHR) cases [3]. This annotation is a very acute pain point, with the process being long, tedious, and prone to error. These alone are obstacles but there is also a problem of chronic understaffing of first responders like police [4], these issues together mean that potential outreach could take longer than it needs to in cases that are potentially very time sensitive. That is why developing tools for automatic annotation and classification would be of great benefit to not just first responders, but also people with BHR issues. Some approaches to this have been tried using NLP techniques but most of the previous attempts have not taken into account the fact that these BHR cases often feature specific language and structure, and in previous endeavors the multi class nature of these accounts was forgone and were put exclusively under a single category for what type of BHR class it was, which is not representative of these reports' complex reality.

Report	Input	Target	Co-oc.	Input Target
'Suspect was in possession of crack, marijuana, and Risperdal. He seemed erratic...'	Types	Class	★ ★ ★	(DRU, SITMH, MED Substance Abuse)
	Keywords	Class	★ ★ ★ ★	(Crack, Marijuana, Erratic, Risperdal Substance Abuse)
	Keywords	Types	★ ★	(Crack, Marijuana DRU)

Fig.1 Framework for Behavioral Health Classifier

Research Question

The research question was as to whether or not a network trained on combined embeddings of models analyzing correlations between different statistics, behavioral health experts curated keywords, evidence types within a report, and the class type of the report, would perform well in multi class classification of police reports.

Materials and Methods

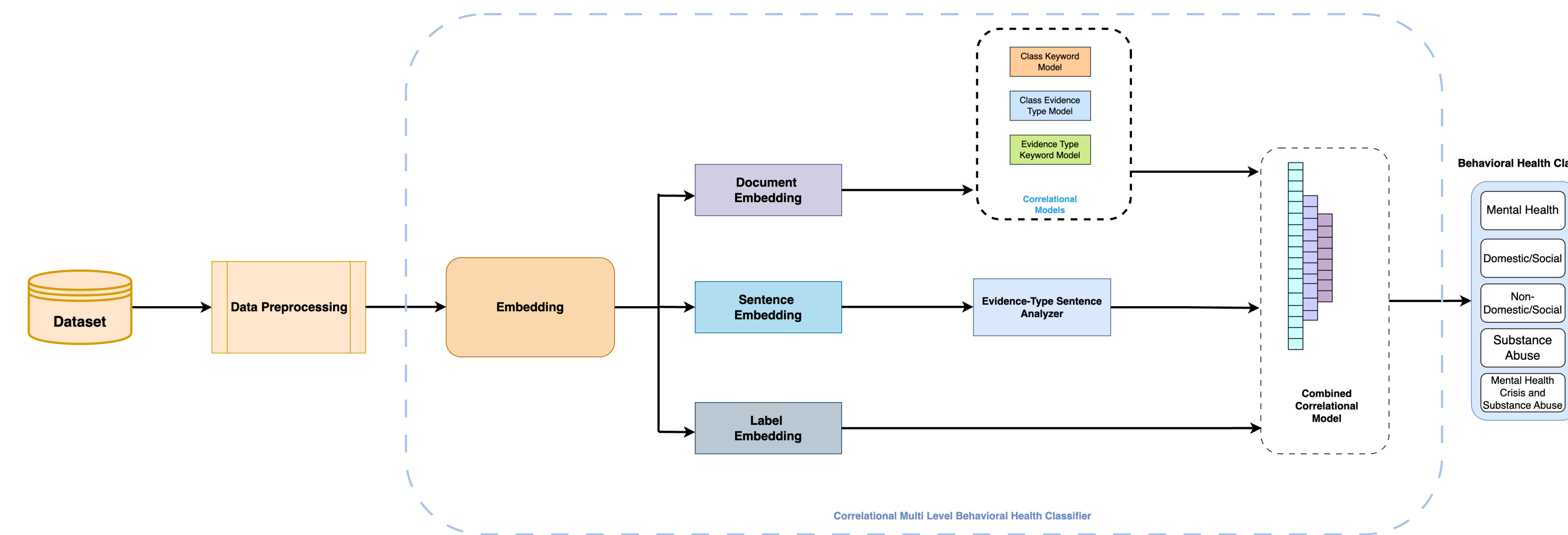


Fig.2 Framework for Behavioral Health Classifier

The model put forth works by using the combined embeddings of models trained on the correlation between different statistics to train a Feed Forward Network (FFN). First the reports were sifted for relevant keywords and sentences including these relevant keywords. We then created a co-occurrence matrix for each report which would count the occurrence of some statistic in a certain field and were . The three co-occurrence matrices were keywords given class, keywords given evidence type, and evidence type given class. The co-occurrence frequency in this case is used to represent the correlation. We then put those co-occurrence matrices through an FFN that would try to predict the correlation of a target feature when given an input. We also trained a FFN on predicting evidence type when given a sentence. After training these FFNs we concatenated their embeddings along with embeddings of labels to capture the semantic meaning and then trained a network on those embeddings.

Results

Model	Accuracy
BiLSTM	38 %
BERT	58 %
RoBERTa	61 %
Proposed Framework	72 %

Fig.3 Table of Accuracy rates of other state of the art models, BiLSTM, BERT [5], RoBERTa [6]

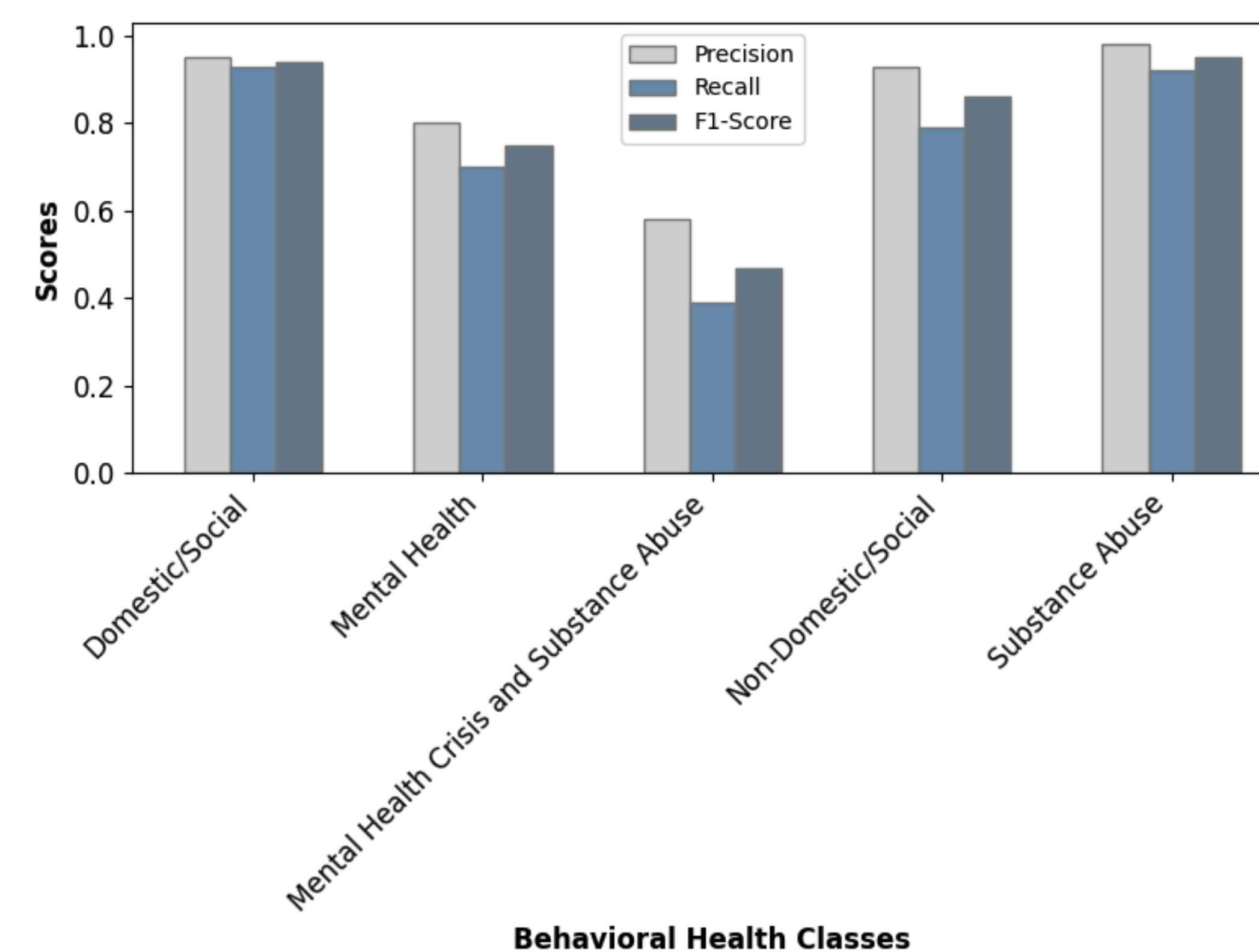


Fig.4 Precision, Recall, and F1-Score of our model on the different BHR classes

On DATE1 at TIME1 I was dispatched to CARDINAL1 FAC1, GPE1, GPE2 at the "FAC2" apartment complex in reference to a domestic dispute. Upon my arrival I met with PERSON1 and her sister PERSON2. PERSON3 advised her boyfriend, PERSON4, was intoxicated...

True Classes:

Domestic/Social

Predicted Classes:

Domestic/Social

(a) Correct Classification

On DATE1 at TIME1, I arrived at 5115 Buckline Ct in reference to the residents inside smoking marijuana. I walked up to the door through CARDINAL1 different vehicles in the driveway and immediately could smell the odor of marijuana

True Classes:

Substance Abuse

Predicted Classes:

Domestic/Social

Mental Health

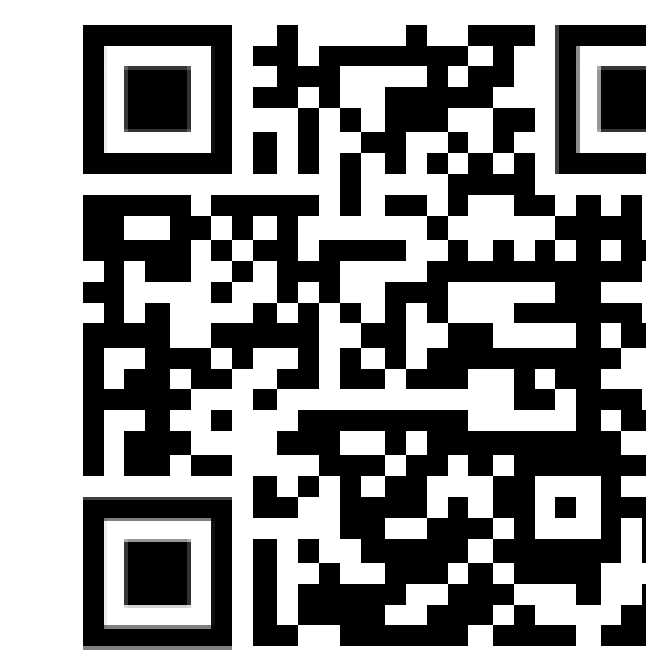
(b) Incorrect Classification

Fig.4 An example of a correctly classified report versus an incorrectly classified report

Conclusions

The model showed a lot of potential with its high-performance rate compared to other SOTA methods, there is potential that when fine tuned and with a better understanding of how each smaller model's correlation affects the overall accuracy of the model, that we could achieve an even higher accuracy. A major bottleneck to the whole project is that some of the BHR classes have very small datasets so there is a limit as to how accurate we can get it for certain classes at least as of right now.

Contact Information



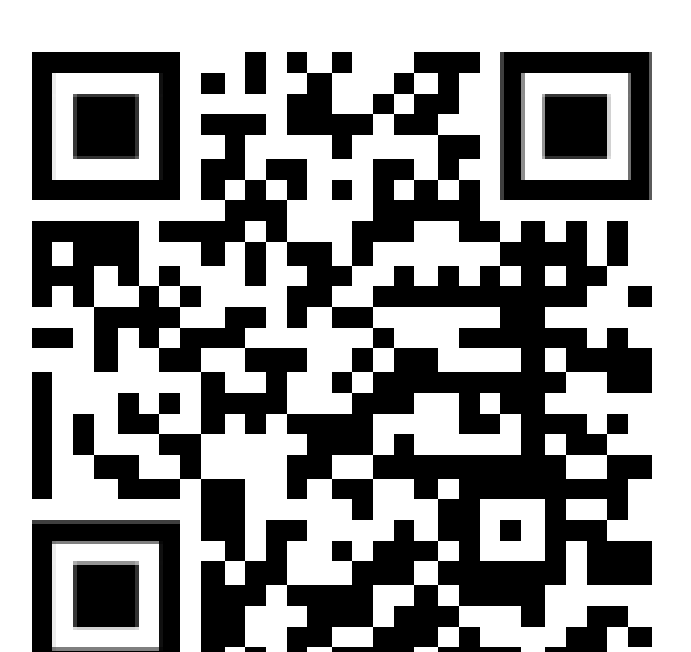
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