# Time-Stealed, or how social medias are stealing our lives

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**Abstract**

The purpose of this project was to show that Bayesian Networks can be an effective tool for extracting relevant information from a domain of interest. Specifically, I wanted to use them to highlight the addictive traits of social media consumption.
I have chosen a (synthetic) dataset containing information about users and their social media usage. Then, I have build different Bayesian Networks to represent the relationships between some selected variables. I have analyzed their structure and, finally, I have queried them with some exact inferences.
I found that all Bayesian Networks, although diversely build, represented the domain of interest with coherence.

## Introduction

### Domain

"Excessive and compulsive online social networking behavior has recently been suggested as a behavioral addiction, although it is not formally recognized or embedded in current psychiatric nosology" (Andreassen 2015). This is how the most cited scholar on cyberpsychology (Pellegrino, Stasi, and Bhatiasevi 2022) introduces her comprehensive review of the current research about social media addiction. In this article, Andreassen stresses the similar effects induced by behavioral addictions like gambling and excessive and compulsive social media use. In fact, symptoms like salience, tolerance, mood alterations, conflict, withdrawal, and relapse are easily identifiable in subjects with an intense social media consumption habit.

### Aim

This project aims at showing how Bayesian Networks can be build, analyzed and queried to effectively model and investigate social media consumption. Particularly, it focuses on presenting different building techniques and on examining the structure and the performance of their resulting networks.

### Method

A Kaggle dataset was first imported, pre-processed and analyzed. Then, pgmpy functions were used to build different Bayesian Networks and to examine how each one of them interpreted the domain of interest. Finally, the same three inferences were run on the three networks to compare their results.

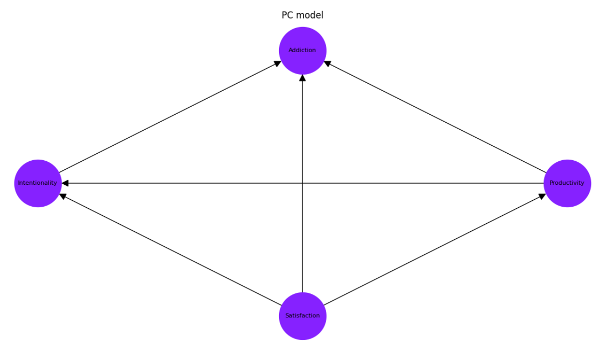


Figure 1: Bayesian Network obtained with PC algorithm

### Results

It seems that different building techniques result in remarkably different Bayesian Networks that nonetheless return similar results when queried. The networks seem to be coherent with the domain knowledge because the inferences highlight the problematic traits of social media consumption.

## Model

The selected variables are pretty self-explanatory, but for any doubt, consult the .ipynb file for a brief description of them. Regarding CPTs, again, consult the .ipynb file as they are plenty and take too much space.

The three Bayesian Networks were build respectively with the PC algorithm[1] (Figure 1), the Tree Search[2] (Figure 2) and the following custom approach (Figure 3) where these were the added links:

[1] `https://www.bnlearn.com/bnrepository/`
[2] `https://pgmpy.org/structure_estimator/tree.html`

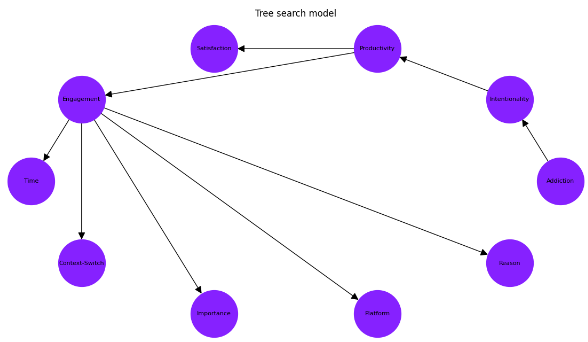


Figure 2: Bayesian Network obtained with Tree Search

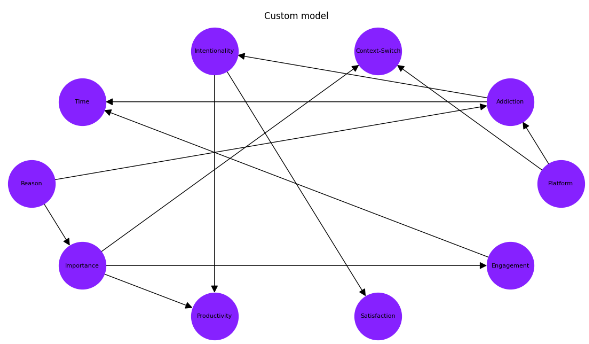


Figure 3: Custom Bayesian Network

- Platform → Addiction: addiction depends on platform as certain platforms are more addictive than others
- Reason → Addiction: addiction depends on reason as compulsive behaviors are triggered by specific situations
- Addiction → Intentionality: intentionality depends on addiction as compulsive behaviors are little intentional by definition
- Reason → Importance: importance depends on reason as social medias can be used for different purposes
- Importance → Engagement: engagement depends on importance as compelling content is more engaging
- Importance → Context-Switch: context-switch depends on importance as compelling content retains users' attention more
- Platform → Context-Switch: context-switch depends on platform as different platforms have different content formats
- Engagement → Time: time depends on engagement as active tasks are more rewarding and therefore more captivating
- Addiction → Time: time depends on addiction as quitting a compulsive behavior is hard by definition
- Importance → Productivity: productivity depends on importance as consuming compelling content can be productive
- Intentionality → Productivity: productivity depends on intentionality as unintentional behaviors rarely align with users' goals
- Intentionality → Satisfaction: satisfaction depends on intentionality as intentionally achieving a goal is satisfying

# Analysis

## Experimental setup

Once the Bayesian Networks were build, they were analyzed with some pgmpy functions that identified d-separations, immoralities, local semantics and Markov blankets. Consequently, three inferences were run on each network:

1. What is the probability that an addicted user has long sessions?
2. What is the probability that an addicted user has unproductive sessions?
3. What is the probability that an addicted user has unsatisfying sessions?

Each one of these required the computation of cumulative probabilities, so it was necessary to set some thresholds to define high and low levels. Computations were done with variable elimination.

## Results

The different building techniques resulted into diverse networks that still were coherent with the domain knowledge. Furthermore, their answers differed just slightly. They returned: 0.8109999999999973 (PC), 0.8426966292134838 (TS) and 0.8277853758001459 (CUSTOM) w.r.t the first inference; 0.9936625243872045 (PC), 0.9936625243872045 (TS) and 1.0 (CUSTOM) w.r.t. the second inference; 0.0 (PC), 0.0 (TS) and 0.0 (CUSTOM) w.r.t. the third inference. These results lead to think that users addicted to social medias are likely to have long sessions of unproductive content consumption and be totally satisfied about it. Specifically, the first two inferences returned high values of probabilities, as expected, while the third one returned 0.0 out of all the networks, which surprised me as I thought that doomscrolling would produce a sense of dissatisfaction and guilt in the user.

# Conclusion

The major limitations to this project were due to the synthetic nature of the dataset[3] and the lack of details pertaining the variables domains. Nevertheless, I picked it because it was the only one I could find that involved the variables I was interested into.

A part from this, Bayesian Networks proved to be valuable tools for modeling and investigating social media consumption. They too confirmed that these platforms have a scary dark side that should definitively be addressed.

[3] `https://www.kaggle.com/datasets/muhammadroshaanriaz/time-wasters-on-social-media?resource=download`

## Links to external resources

- Github repo: https://github.com/Jtries/socialMediaBayes
- Kaggle dataset: https://www.kaggle.com/datasets/muhammadroshaanriaz/time-wasters-on-social-media?resource=download

## References


Andreassen, C. S. 2015. Online social network site addiction: A comprehensive review. *Current addiction reports* 2(2):175–184.

Pellegrino, A.; Stasi, A.; and Bhatiasevi, V. 2022. Research trends in social media addiction and problematic social media use: A bibliometric analysis. *Frontiers in psychiatry* 13:1017506.