

## Analyzing Happiness: Investigation on Happy Moments using a Bag-of-words Approach and Related Ethical Discussions

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- Analysis of moments and activities making people happy, based on a collection of "happy moments"
  - *"I watched a great TV show while petting my cat today"*
  - "I woke up today"
- A collection of text responses shared through Amazon Mechanical Turk (MTurk)
  - Crowd-sourcing platform
- Possibility of predicting people's happiness
  - by gathering data from personal experiences and the correlation of the emotion felt
- Through this data analysis and investigation procedure, we have quantitatively and qualitatively studied reasons that make certain group of people happy.
  - Impactful in helping the broader society
  - Impactful for companies



- <u>Process</u>: Started with previous studies conducted on crowd-sourcing, the behavior of online decision making, and the study of human factors of happiness
- Motivation: Growing issue and importance of mental health <sup>1</sup>
- Platform: Crowd-sourcing, one of the most efficient methods for analyzing online decision making <sup>2</sup>
  - <u>Literature:</u> Life events affect people's happiness levels <sup>3</sup>
    broad spectrum of events, ranging from health, relationships, employment, money and other
- Approaches:
  - Sensor-based <sup>4</sup>
  - Text-based

![](_page_3_Picture_0.jpeg)

- <u>RQ1:</u> Can we predict the reason of happiness from a person's happy moment?
  - Based on this dataset, are we able to accurately predict happiness category in the past 24 hours or 3 months?
  - What was misclassified? Why?
- <u>RQ2:</u> By looking at specific subgroups (*certain country, age, gender, etc.*), what are the reasons of happiness in that group?

**Dataset:** Description

#### HappyDB<sup>5</sup>:

- a collection of crowd-sourced happy moments
- 100,922 happy moments, 10,843 distinct participant
- Tables: cleaned\_hm, demographic
- <u>Cleaned\_hm:</u> 100,535 observations and 9 variables
  - Reflection period (24 hrs or 3 months)
  - Happy moment text
  - Ground truth category (Achievement, Affection, Bonding, Enjoying the moment, Exercise, Leisure, Nature)
  - Number of sentences
- Demographic: 10,844 observations and 6 variables
  - Age, country, gender, marital status, parenthood
- Cleaning and preprocessing:
  - Removal of *null*, invalid age, misspellings and wrong texts
  - Equal width binning: Age (17-20, 21-30, 31-40, 41-50, 51-60, 60+)

![](_page_5_Picture_0.jpeg)

#### Dataset: Exploratory

![](_page_5_Figure_2.jpeg)

Fig: Gender distribution in participants vs contributors

![](_page_5_Figure_4.jpeg)

Fig: Marital status distribution in participants vs contributors

![](_page_5_Figure_6.jpeg)

Fig: Parenthood distribution in participants vs contributors

	17-20	21-30	31-40	41-50 age_ca	51-60 ategory	61+	NaN	prefer not to say
achievement *								
affection -								
bonding -								
injoy_the_moment -								
exercise -								
leisure -								
nature -								
Α	ge_category	VS Predicted	_category					

Fig: Age group vs happiness category

Data **Methods** 

- About two-thirds of our categories being made up by affection and achievement
- Bag-of-words approach
  - 25,400 columns
  - $\qquad \qquad \mathsf{Count vectorizer} \to \mathsf{TF}\mathsf{-}\mathsf{IDF}^{\mathsf{T}}$
- Linear Support Vector Classifier
  - 75:25 train-test split
  - Accuracy plateau at around 5,000 features
- We used 6,700 features for our model to obtain best accuracy (~94% on average)

![](_page_6_Figure_9.jpeg)

Fig: Accuracy vs number of features

Results

#### Metrics:

Category	Precision	Recall	
affection	0.94	0.95	
enjoy the monent	0.96	0.98	
achievement	0.97	0.95	
bonding	0.88	0.86	
leisure	0.91	0.87	
nature	0.91	0.87	
exercise	0.92	0.89	

Fig: Precision-recall for each category

![](_page_7_Figure_4.jpeg)

Fig: Confusion matrix - Predicted vs actual categories

#### Misclassifications and Context:

- "My students gave me a card"
  - Predicted: Achievement, Ground truth: Bonding
- "Ran my fastest 5K ever!"
  - Predicted: Exercise, Ground truth: Achievement
- <u>Reason 1:</u> Shorter sentences and less meaningful (and common) words used
- <u>Reason 2</u>: Listing multiple moments in the same response

Dissecting Happiness: Case Study 1

#### Married vs Single:

- Group: People who are from 'USA' and talked about happiness in the category 'enjoy the moment' in the last '24 hours'
- Subgroup: Within this group, people married vs. people single

![](_page_8_Figure_4.jpeg)

Fig: Top 10 trigrams from each group

#### Findings:

- Food: 'ate great steak' vs 'pizza for dinner'
- Social contexts: Food priorities, Financial Conditions, Social status
- Example: 'The delicious steak that I had for dinner tonight made me very happy.' vs. 'I ordered two of my favorite pizzas from Pizza Hut and it was cooked just right.'

Dissecting Happiness: Case Study 2

#### Parents vs. Non-parents:

- Group: People who are from 'USA' and talked about happiness in the category 'enjoy the moment' in the last '24 hours'
- Subgroup: Within this group, parents vs. non-parents

![](_page_9_Figure_4.jpeg)

#### Findings:

- Sleep: 'able to sleep' , 'to sleep in'
- Example: 'I got a full night of sleep. That does not often happen with a 3 month-old in the house.'

![](_page_10_Picture_0.jpeg)

- Data Collection
  - Informed consent, Collection bias, Limit PII exposure
- Data storage
  - Data security, Right-to-be-forgotten, Data retention plan
- Analysis
  - Missing perspective, Honest representation, Privacy in Analysis, Explainability, Auditability, Fairness across groups
- Deployment
  - Concept drift, Unintended use

![](_page_11_Picture_0.jpeg)

- Happiness through 'happy moments'
- Detection of 'category' of happiness
- Reasons for happiness
- Social and ethical implications
- Future work
  - Bigger dataset, more emotions (disgust, anger, sadness)
  - Applied work: sentiment analysis tool
  - Better classification algorithm

![](_page_12_Picture_0.jpeg)

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![](_page_13_Picture_0.jpeg)

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# THANKS!

### Any questions?

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