



HUMOR & SARCASM DETECTION

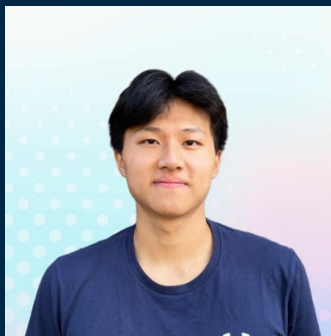
Presented by
The Anti-Sarcasm Sarcastic Club

MEET THE CLUB



CHRISTOPHER
“Boat Boy”
MOPPEL

Grinnell College, '23



JOHN
“LeetCode”
BILLOS

Wake Forest, '24



YUSUF
“Edgy Jokes
Trained the
Model” **ISMAIL**

Carleton College, '24

ALBERT
“Not Geoffrey”
JING

Carleton College, '25

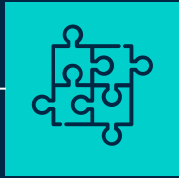


GEOFFREY
“Not Albert”
JING

Carleton College, '25



PRESENTATION OUTLINE



01

DESCRIPTION &
MOTIVATION



02

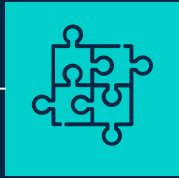
PREVIOUS RELATED
WORKS



03

DATA CLEANING &
PREPROCESSING

PRESENTATION OUTLINE (cont.)



04

MODEL
ANALYSIS



05

LIVE
DEMO



06

NEXT
STEPS

DESCRIPTION & MOTIVATION

01

The background is a dark blue gradient. It is decorated with various geometric elements: thin white vertical lines of varying lengths, small squares in teal, orange, and pink, and larger squares in teal and orange. The text is centered and reads:

HUMOR & SARCASM DETECTION?



OUR PROCESS

30K News Headlines
labeled as
Sarcastic/Humorous
or not

DATA

MODELING

Build suite of different
models: Neural
Networks, kNN, Naive
Bayes, XGBoost,
Random Forest, etc.

Evaluate performance
of all models on
cleaned dataset and
determine highest
performing model

EVALUATION

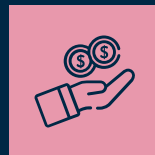
TUNING

Fine-tune
hyperparameters of
the winning model

OUR MOTIVATION

CHALLENGE

Humor & Sarcasm
Detection is still an
active field of research

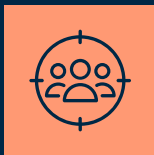


OPEN-ENDED

Always room for
improvement
(ex. text-scraping)

TWIN ID FAILED

Can we design a
facial-rec model to
distinguish between
Geoffrey & Albert?



LEARNING

New modelling and
data-transformation
techniques

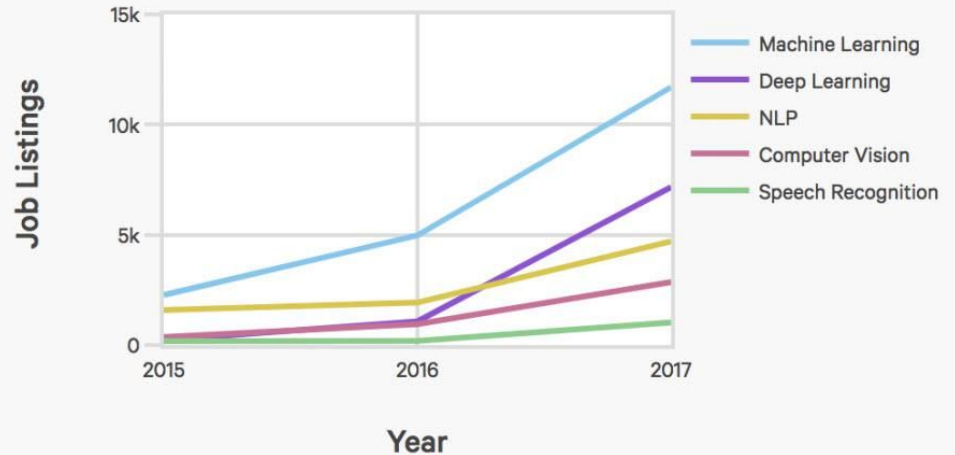
PREVIOUS RELATED WORKS

02

AI Market Trends



Job Openings, Skills Breakdown (Monster.com)



Communication with Machines

```
Welcome to

EEEEEE LL IIII ZZZZZZ AAAAA
EE LL II ZZ AA AA
EEEEEE LL II ZZZ AAAAAA
EE LL II ZZ AA AA
EEEEEE LLLLLL IIII ZZZZZZ AA AA

Eliza is a mock Rogerian psychotherapist.
The original program was described by Joseph Weizenbaum in 1966.
This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?
YOU: Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU: They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU: Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU: It's true, I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:
```

50s-70s



90s

M What is the best burger recipe?

There are many different burger recipes out there, and the "best" one will depend on personal preference. Some people prefer their burgers to be simple and classic, while others like to experiment with different ingredients and flavors.

Here is a basic burger recipe that can serve as a starting point:

Ingredients:

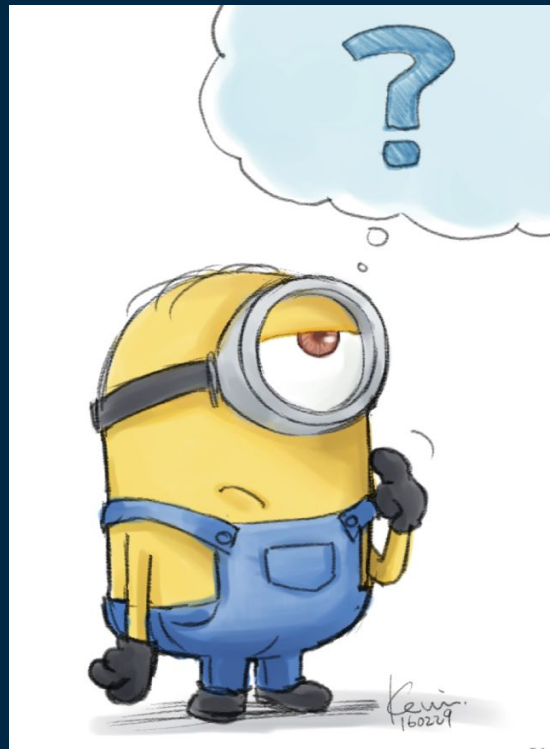
- 1 pound ground beef
- 4 hamburger buns
- Lettuce, tomato, onion, and other toppings of your choice
- Salt and pepper

Instructions:

Today

WHY IS NLP HARD?

1. Ambiguity
2. Scale
3. Sparsity
4. Variation
5. Expressivity
6. Unknown representations



NLP TODAY



ASSISTANT

Hi, how can I help?

Daily News Headlines

8 years from 2008-2016



Dow Jones

Industrial Average(DJIA)
Same day close value



OpenAI

Sarcasm Detection: A Comparative Study

July 2021

License · [CC BY 4.0](#)

Authors:



Hamed Yaghoobian



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University of Georgia



Khaled Rasheed
University of Georgia

Machine Learning-Based Model for Sentiment and Sarcasm Detection

Hamada Nayel, Eslam Amer, Aya Allam, Hanya Abdallah

ChatGPT: Optimizing Language Models for Dialogue

On the naturalness of fuzzer-generated code

Authors: [Rajeswari Hita Kambhamettu](#), [John Billos](#), [Tomi Oluwaseun-Apo](#), [Benjamin Gafford](#), [Rohan Padhye](#), [Vincent J. Hellendoorn](#) [Authors Info & Claims](#)

On the naturalness of software

Authors: [Abram Hindle](#), [Earl T. Barr](#), [Mark Gabel](#), [Zhendong Su](#), [Premkumar Devanbu](#) [Claims](#)

Sarcasm Analysis and Mood Retention Using NLP Techniques



January 2022 · [International Journal of Information Retrieval Research](#) 12(1):23
DOI: [10.4018/IJIRR.289952](#)

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RCC Institute of Information Technology

TECHNOLOGIES

NAME

DESCRIPTION

EXAMPLES

NATURAL LANGUAGE PROCESSING

Subfield of linguistics, Computer Science and AI concerned with the interactions between computers and human language.

Speech Recognition, etc.

NEURAL NETWORKS

Artificial network of artificial neurons (perceptrons) used for solving AI problems.

Convolutional (CNN), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), etc.

DATA ENCODING

Process of transforming data into a digestible format for regression (NN) algorithms.

N-grams, TF-IDF, etc.

ADVANCED ML ALGORITHMS

Advanced regression techniques tailored towards NLP problems.

XGBoost, BERT, Word2Vec, etc.

DATA CLEANING & PREPROCESSING

03

The background is a dark blue field decorated with various geometric elements. There are numerous small squares in white, teal, and pink. Some of these squares are connected to the top edge of the frame by thin, vertical white lines, creating a sense of depth or suspension. The overall aesthetic is modern and minimalist.

WHAT IS HUMOR ANYWAY?

HUMOR EXPLAINED

Humor: the capacity to express or perceive what's funny, is both a source of entertainment and a means of coping with difficult or awkward situations and stressful events.

Sarcasm: a type of phenomenon with specific perlocutionary effects on the hearer, such as to break their pattern of expectation.



Correct understanding of humor/sarcasm requires an understanding of the utterance, the conversational context, and, frequently some real-world facts.

DATA ENCODING TECHNIQUES



Bag of Words



Count Vectorization



N-Grams



TF-IDF



Word2Vec



BERT

DATASET

News Headlines Dataset For Sarcasm Detection

High quality dataset for the task of Sarcasm and Fake News Detection



30,000

Observations

(Individual Headlines)

3

Datapoints/Observation

1. Headline (string)
2. Link to the Article (hyperlink)
3. Humorous/Sarcastic? (binary)

2

News Sources

1. The Onion
2. HuffPost

SAMPLE OBSERVATION (RAW)

Sarcastic/Humorous:

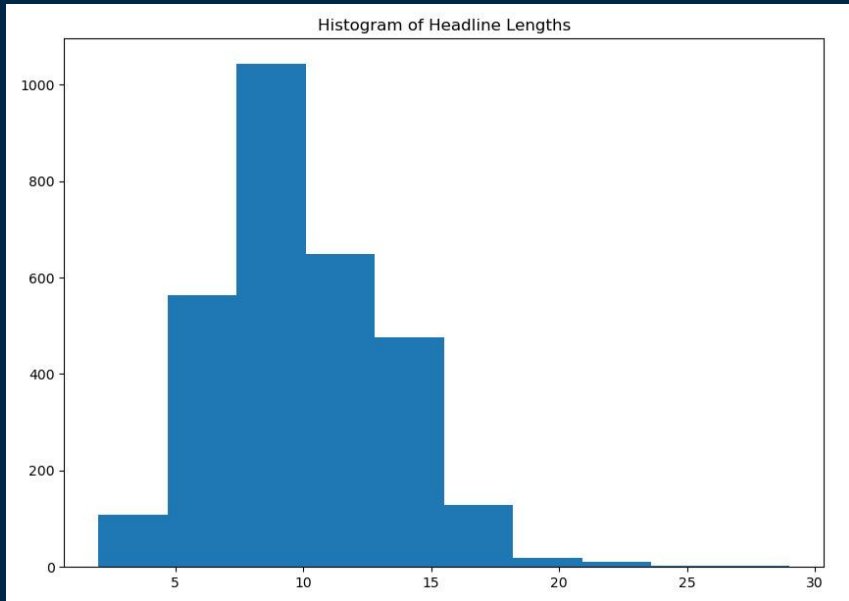
```
is_sarcastic      1
headline          mother comes pretty close to using word 'strea...
article_link      https://www.theonion.com/mother-comes-pretty-c...
Name: 4, dtype: object
```

Not Sarcastic/Humorous:

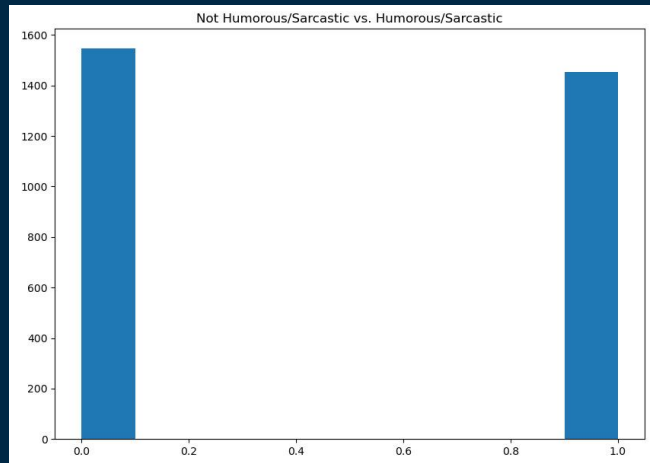
```
is_sarcastic      0
headline          eat your veggies: 9 deliciously different recipes
article_link      https://www.huffingtonpost.com/entry/eat-your-...
Name: 2, dtype: object
```

DATASET SUMMARY

STATISTICS



Headline Lengths



Sarcastic/Humorous vs. Not Sarcastic/Humorous

DATASET WORD CLOUDS

Sarcastic/Humorous Headlines



Not Sarcastic/Humorous Headlines



MODEL ANALYSIS

04

MODELS

*K Nearest Neighbors
(kNN)*

Naive Bayes

XG Boost

Decision Trees

*Bidirectional Encoder
Representations from
Transformers (BERT)*

*Convolutional Neural
Network (CNN)*

Random Forests

*Long Short Term
Memory Network
(LSTM)*

*Gated Recurrent Unit
Network (GRU)*

Logistic Regression

MODEL PERFORMANCES

	Sarcastic/Humorous Headlines			NOT Sarcastic/Humorous Headlines		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
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<i>kNN</i>	<i>0.53</i>	<i>0.42</i>	<i>0.47</i>	<i>0.56</i>	<i>0.67</i>	<i>0.61</i>
<i>XGBoost</i>	<i>0.63</i>	<i>0.42</i>	<i>0.50</i>	<i>0.59</i>	<i>0.78</i>	<i>0.67</i>
<i>Logistic Reg.</i>	<i>0.79</i>	<i>0.41</i>	<i>0.54</i>	<i>0.63</i>	<i>0.90</i>	<i>0.74</i>
<i>Random Forest</i>	<i>0.62</i>	<i>0.55</i>	<i>0.59</i>	<i>0.63</i>	<i>0.70</i>	<i>0.67</i>
<i>CNN</i>	<i>0.78</i>	<i>0.84</i>	<i>0.81</i>	<i>0.84</i>	<i>0.78</i>	<i>0.81</i>
<i>GRU</i>	<i>0.84</i>	<i>0.81</i>	<i>0.83</i>	<i>0.83</i>	<i>0.86</i>	<i>0.84</i>
<i>LSTM</i>	<i>0.82</i>	<i>0.84</i>	<i>0.83</i>	<i>0.85</i>	<i>0.82</i>	<i>0.84</i>

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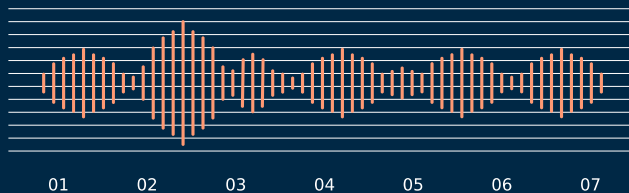
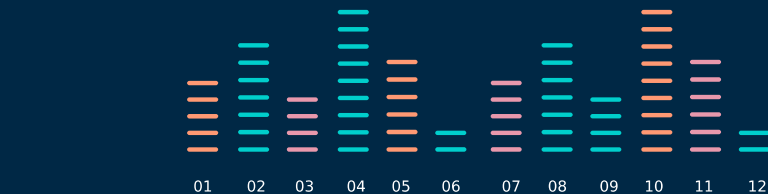
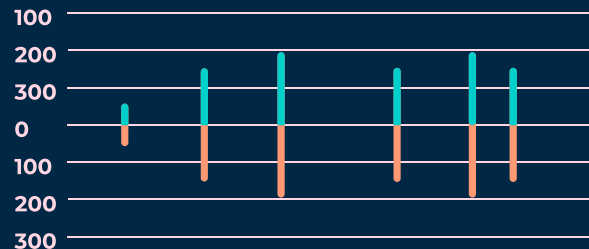
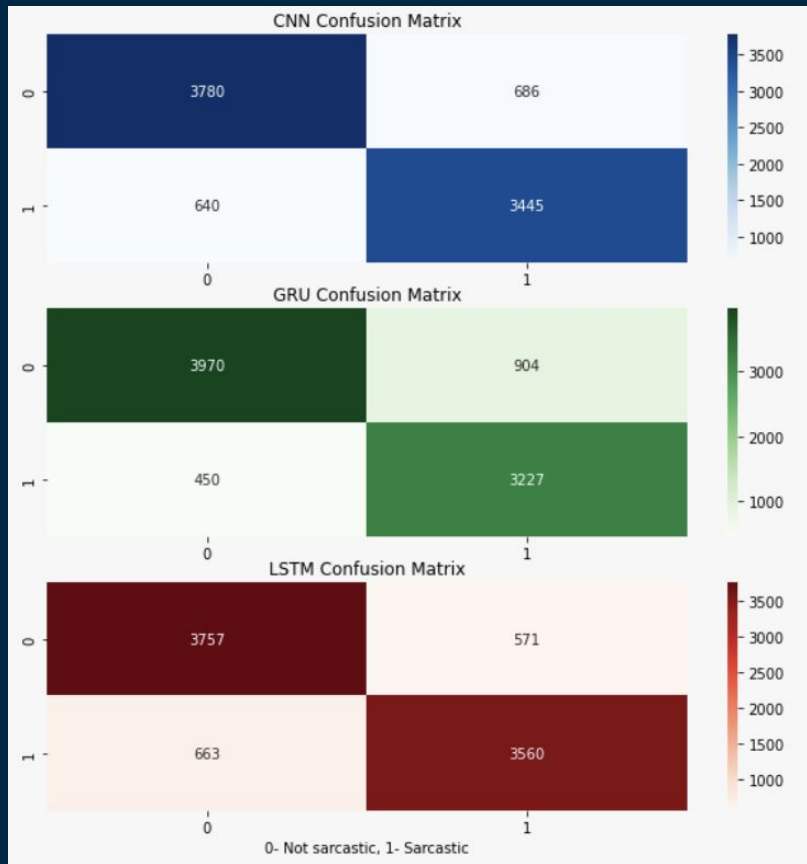
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NEURAL NETWORKS



BERT



BERT

Bidirectional Encoder Representations from Transformers



Example

After stealing money from the bank vault, the bank robber was seen fishing on the Mississippi river bank.

First 5 vector values for each instance of "bank".

bank vault	tensor([3.3596, -2.9805, -1.5421, 0.7065, 2.0031])
bank robber	tensor([2.7359, -2.5577, -1.3094, 0.6797, 1.6633])
river bank	tensor([1.5266, -0.8895, -0.5152, -0.9298, 2.8334])

BERT

94% accuracy

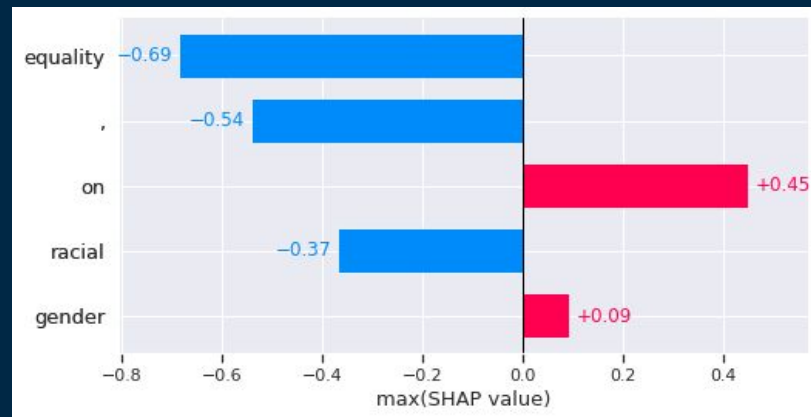


epoch					
1	0.27	0.21	0.92	0:04:33	0:00:10
2	0.12	0.22	0.93	0:04:33	0:00:10
3	0.06	0.23	0.94	0:04:33	0:00:11
4	0.03	0.28	0.94	0:04:33	0:00:11

SHAP explainer

Some words have greater effects than others

Open this [link](#)



BERT

Advantages:

- Very accurate
- Pre-trained
- Versatile, there is multiple versions with multiple datasets that they were trained on
- Easy to fine tune
- Developed by google and has lots of support
- Can be equipped with explainers very easily
- Contextual understanding

Disadvantages:

- Takes very long time to fine tune
- Pytorch is more complicated than tensorflow but explainers are easily adapted into it afterwards
- Much more code than neural networks

LIVE DEMO

05

NEXT STEPS

06

If We Had More Time...

1. Repeat previous analysis with TF-IDF Data Encoding
2. Refine Neural Network Models (CNN, GRU, LSTM)
3. Enhance Neural Network models through web-scraping article content using each observations' hyperlink
4. Investigate Word2Vec Encoding
5. Enhance the BERT encoder

The background is a dark navy blue. It is decorated with various geometric elements: small squares in white, light blue, and orange, and thin vertical lines of the same colors. These elements are scattered across the frame, creating a modern, minimalist aesthetic.

THANK YOU

The background is a dark blue gradient. It is decorated with several vertical white lines of varying lengths. Scattered throughout are small squares in three colors: light blue, pink, and orange. Some squares are solid, while others are outlined.

Questions?

WARNING: If you don't want a sarcastic answer, don't ask a stupid question...

OUR COMPANY

Mercury is the closest planet to the Sun and the smallest one in the Solar System—it's only a bit larger than the Moon. The planet's name has nothing to do with the liquid metal



UNDERSTANDING THE PROBLEM

MARS

Despite being red, Mars is a cold place. It's full of iron oxide dust, which gives the planet its reddish cast

VENUS

Venus has a beautiful name and is the second planet from the Sun. It's terribly hot, even hotter than Mercury



MAIN COMPETITORS

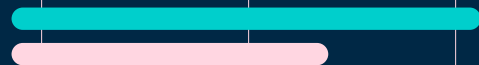
NEPTUNE

It's the farthest planet
from the Sun



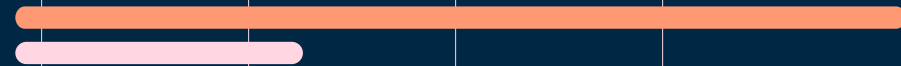
MARS

Despite being red, Mars
is a cold place



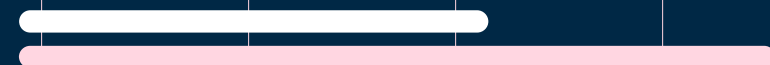
VENUS

Venus is the second planet
from the Sun

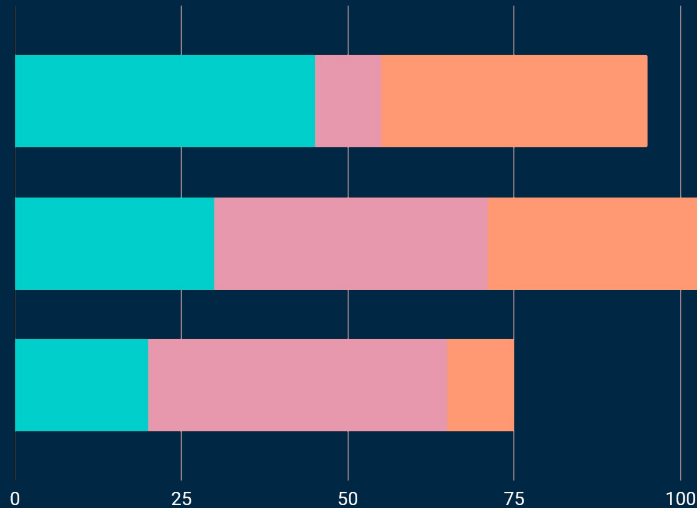


SATURN

It's composed mostly of
hydrogen and helium



MARKET RESEARCH



NEPTUNE

It's the farthest planet from the Sun

MERCURY

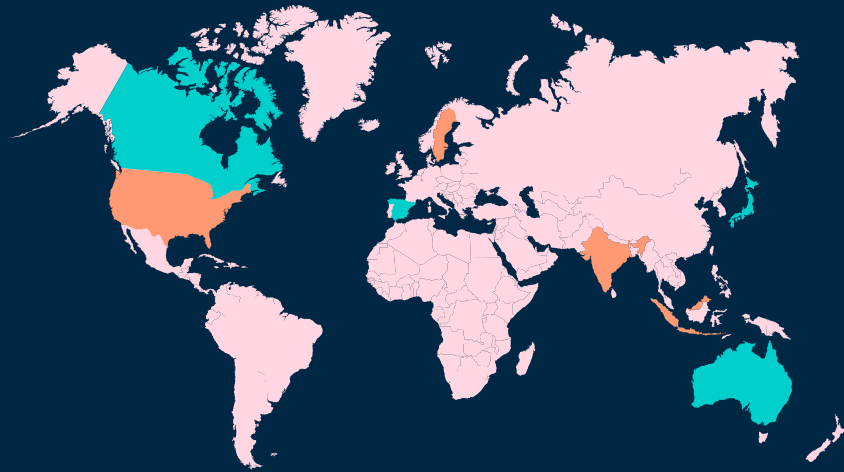
Mercury is the closest planet to the Sun

SATURN

Saturn is composed of hydrogen and helium

ANALYSIS

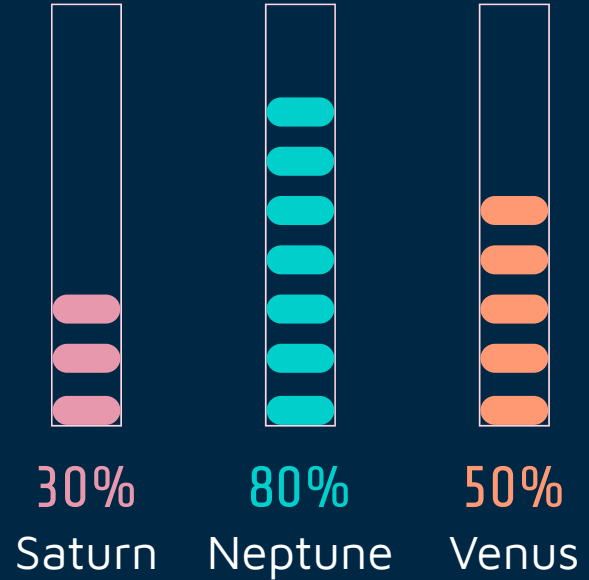
OUTREACH



■ Mars

■ Mercury

TOP RATED VALUES



TARGET

GENDER



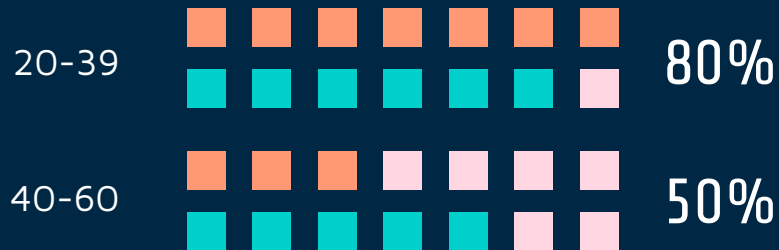
75%

Female

60%

Male

AGE

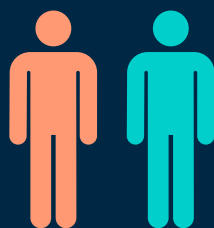


20-39

80%

40-60

50%

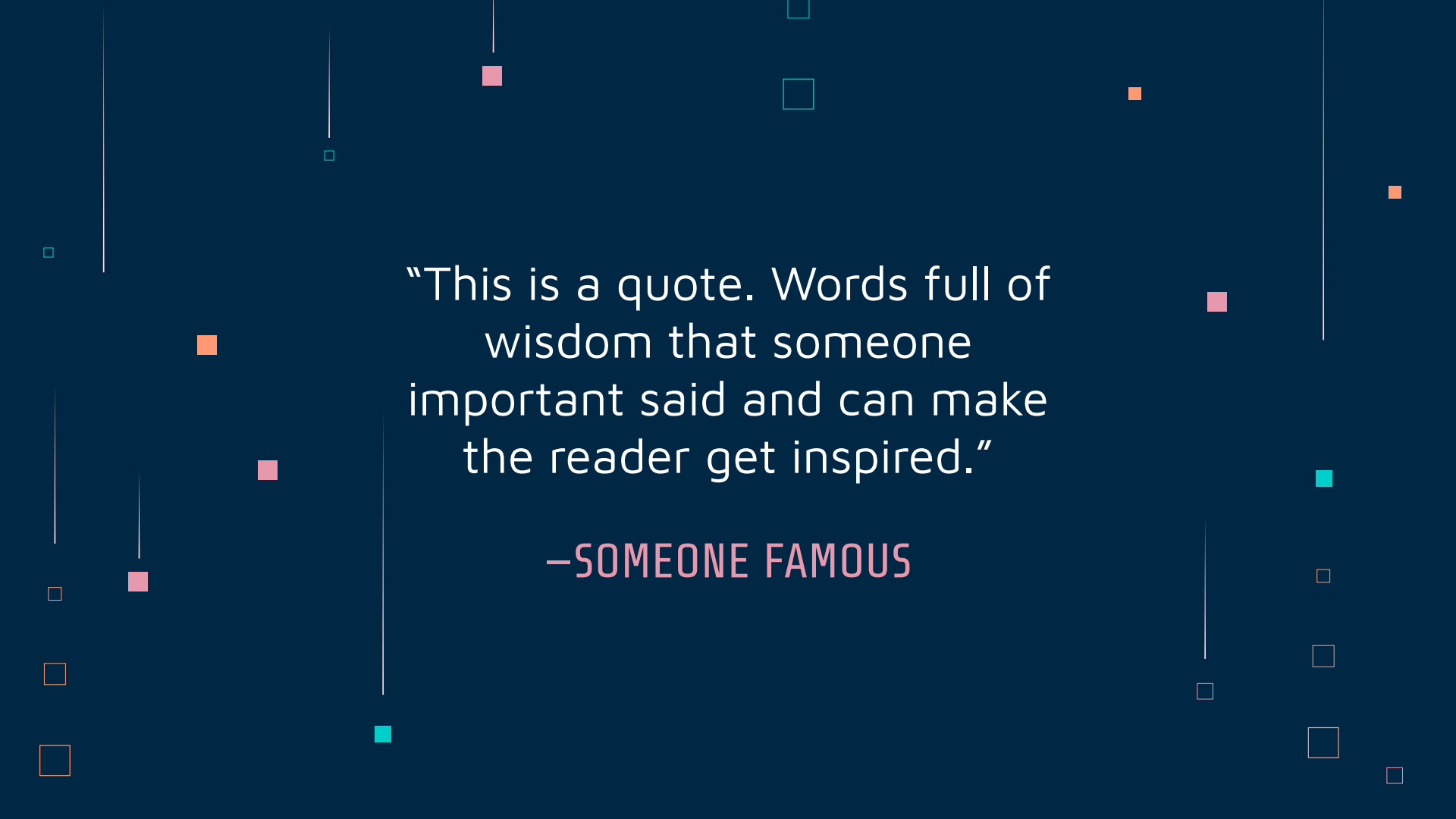


500,000+

Employees



A Picture Is Worth a
Thousand Words

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“This is a quote. Words full of
wisdom that someone
important said and can make
the reader get inspired.”

—SOMEONE FAMOUS

OUR PARTNERS

Venus has an extremely poisonous atmosphere

VENUS

SATURN

Saturn is composed mostly of hydrogen and helium



Despite being red, Mars is actually a cold place

MARS

MERCURY

Mercury is the closest planet to the Sun

TESTIMONIALS



"Mercury is the closest planet to the Sun and the smallest of them all"

—RYAN DIXON



"Saturn is composed mostly of hydrogen and helium"

—BILLY BROOKS



"Venus has a beautiful name and is the second planet from the Sun"

—ALIYA FARLEY



"The Sun is the star at the center of the Solar System"

—LUCY JADE



"Jupiter is a gas giant and the biggest planet in the Solar System"

—HENRY McKANE



"Neptune is the fourth-largest planet in the Solar System"

—ROSE CLARK

4,498,300,000

Big numbers catch your
audience's attention



UPCOMING GOALS

JUPITER

JUNE 2



It's the biggest planet in the Solar System

SATURN

OCTOBER 14



Saturn is composed mostly of hydrogen and helium

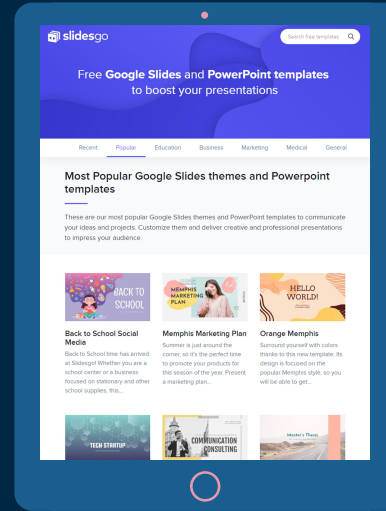
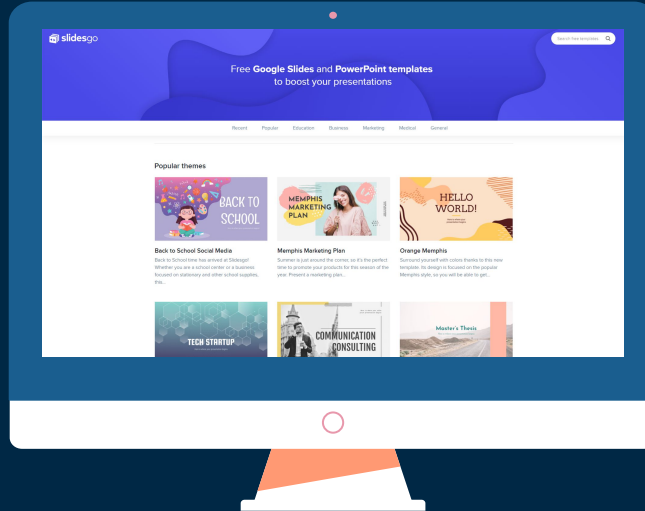
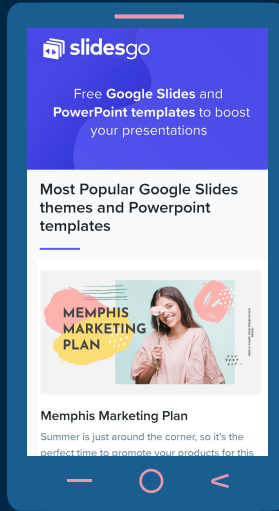
NEPTUNE

JANUARY 23



Neptune is the farthest planet from the Sun

SNEAK PEEK



You can replace the images on these screens with your own work

Do you have any questions?

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yourcompany.com

THANKS



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ALTERNATIVE RESOURCES

