

• • • • • • • •
• • • • • • • •
• • • • • • • •
• • • • • • • •
• • • • • • • •

LUCID: A Practical, Lightweight Deep Learning Solution for DDoS Attack Detection

IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT
2020

-
-
-
-
-

Introduction

- **DDoS** attacks have become more difficult to detect due to the many **combinations** of attack approaches.
 - Traditional **signature-based** intrusion detection systems cannot react to new attacks.
 - Existing **statistical anomaly-based** detection systems are constrained by the requirement to define thresholds for detection.
- **CNN** has advanced the state-of-the-art in certain specific scenarios such as malware detection, network traffic analysis and intrusion detection.
- With the drive towards **edge computing**, it becomes to consider the ability to protect against attacks on resource-constrained devices.

-
-
-
-
-

Contributions

- 1) CNN for online resource-constrained environments to learn the behaviour of DDoS and benign traffic flows with both low processing overhead and attack detection time. → **LUCID** (Lightweight, Usable CNN in DDoS Detection)
- 2) A **dataset-agnostic preprocessing mechanism** that produces traffic observations consistent with those collected in existing online systems
- 3) A **kernel activation analysis** to interpret and explain to which features LUCID attaches importance when making a DDoS classification.
- 4) An **empirical validation** of LUCID on a resource-constrained hardware platform to demonstrate the applicability of the approach in edge computing scenarios, where devices possess limited computing capabilities.

Proposed Method

- Network Traffic Preprocessing

Why

shared nature of the communication link → packets from different data flows are multiplexed resulting in packets from the same flow being separated for transmission

So what

the processing for live presentation of traffic to a NIDS is quite different to the processing of a static dataset

solve

converting the traffic flows in a dataset into array-like data structures and splits them into sub-flows based on time windows

Network Traffic Preprocessing

- Features extraction

Pkt #	Time (sec) ¹	Packet Len	Highest Layer ²	IP Flags	Protocols ³	TCP Len	TCP Ack	TCP Flags	TCP Window Size	UDP Len	ICMP Type
0	0	151	99602525	0x4000	0011010001000b	85	336	0x018	1444	0	0
1	0.092	135	99602525	0x4000	0011010001000b	69	453	0x018	510	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
j	0.513	66	78354535	0x4000	0010010001000b	0	405	0x010	1444	0	0
$j + 1$	0	0	0	0	000000000000000b	0	0	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
n	0	0	0	0	000000000000000b	0	0	0	0	0	0

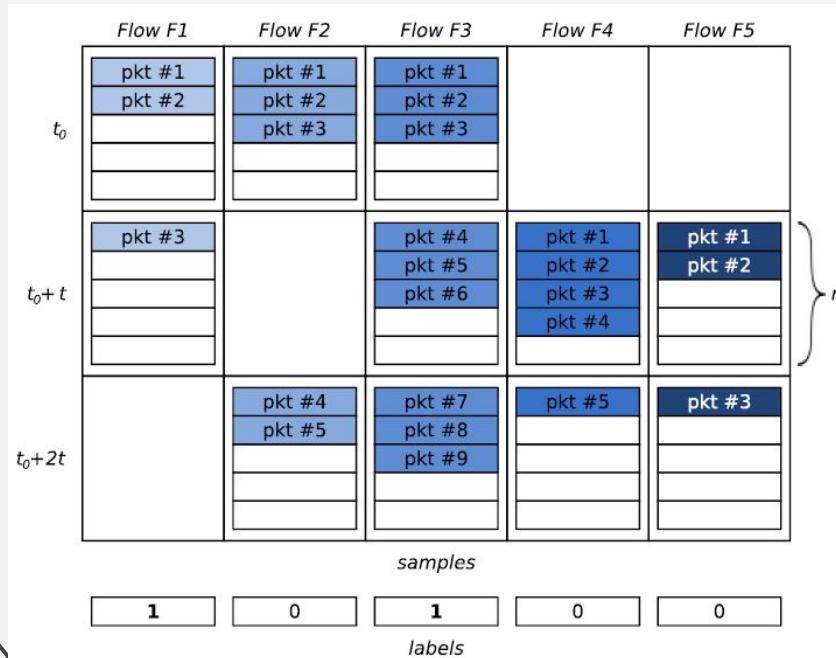
Network Traffic Preprocessing

- Normalization and padding

Pkt #	Time (sec) ¹	Packet Len	Highest Layer ²	IP Flags	Protocols ³	TCP Len	TCP Ack	TCP Flags	TCP Window Size	UDP Len	ICMP Type
Packets	0	151	99602525	0x4000	0011010001000b	85	336	0x018	1444	0	0
	1	135	99602525	0x4000	0011010001000b	69	453	0x018	510	0	0
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	j	0.513	66	78354535	0x4000	0010010001000b	0	405	0x010	1444	0
Padding	$j + 1$	0	0	0	0	000000000000000b	0	0	0	0	0
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	n	0	0	0	0	000000000000000b	0	0	0	0	0

Network Traffic Preprocessing

- Data processing algorithm



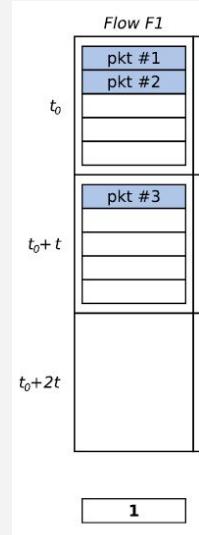
simulates the traffic capturing process of online IDSs
→ the traffic is collected for a certain amount of time t before being sent to the anomaly detection algorithms.

Algorithm 1 Network Traffic Preprocessing Algorithm

Input: Network traffic trace (NTT), flow-level labels (\mathcal{L}), time window (t), max packets/sample (n)

Output: List of labelled samples (\mathcal{E})

```
1: procedure PREPROCESSING( $NTT, \mathcal{L}, t, n$ )
2:    $\mathcal{E} \leftarrow \emptyset$             $\triangleright$  Initialise the set of samples
3:    $\tau \leftarrow -1$            $\triangleright$  Initialise the time window start-time
4:   for all  $pkt \in NTT$  do       $\triangleright$  Loop over the packets
5:      $id \leftarrow pkt.tuple$          $\triangleright$  5-tuple flow identifier
6:     if  $\tau == -1$  or  $pkt.time > \tau + t$  then
7:        $\tau \leftarrow pkt.time$        $\triangleright$  Time window start time
8:     end if
9:     if  $|\mathcal{E}[\tau, id]| < n$  then     $\triangleright$  Max  $n$  pkts/sample
10:       $\mathcal{E}[\tau, id].pkts.append(pkt.features)$ 
11:    end if
12:  end for
13:   $\mathcal{E} \leftarrow normalization\_padding(\mathcal{E})$ 
14:  for all  $e \in \mathcal{E}$  do           $\triangleright$  Labelling
15:     $e.label \leftarrow \mathcal{L}[e.id]$   $\triangleright$  Apply the label to the sample
16:  end for
17:  return  $\mathcal{E}$ 
18: end procedure
```

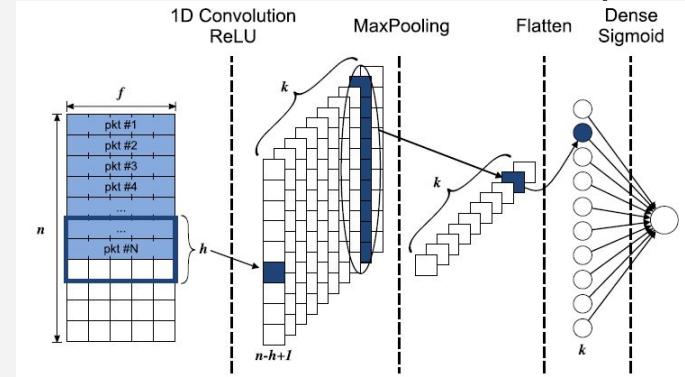


α	Learning rate	n	Number of packets per sample
f	Number of features per packet	s	Batch size
h	Height of convolutional filters	t	Time window duration
id	5-tuple flow identifier	τ	Time window start time
k	Number of convolutional filters	\mathcal{E}	Array of labelled samples
m	Max pooling size	\mathcal{L}	Set of labels

LUCID Model

- Objective: minimise the complexity and performance time of CNN model for feasible deployment on resource-constrained devices.
- Input: $F = [n \times f]$ (a traffic flow)
- CNN layer:
 - k filters of size $h \times f$ → extract and learn local features
 - Activation map $a_k = \text{ReLU}(\text{Conv}(F) W_k, b_k)$
 - Activation matrix A of size $(n-h+1) \times k$
- Max pooling, flatten
- Output: sigmoid
 - $P > 0.5 \rightarrow \text{DDoS}$
- Loss function

$$c = -\frac{1}{s} \sum_{o=1}^s (y_o \log p_o + (1 - y_o) \log(1 - p_o))$$



-
-
-
-
-

Datasets

- ISCX2012, CIC2017 and CSECIC2018

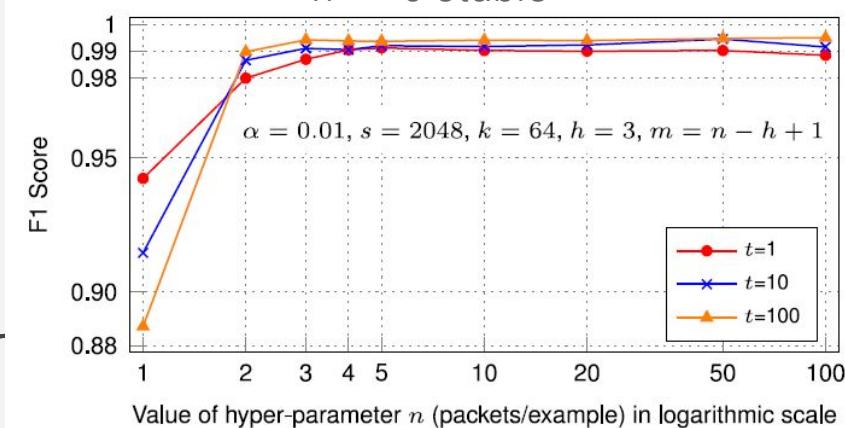
Dataset	Traffic trace	#Flows	#Benign	#DDoS
ISCX2012	Tue15	571698	534320	37378
CIC2017	Fri7PM	225745	97718	128027
CSECIC2018	Wed21	1048575	360832	687743

- Data processing algorithm → UNB201X
- 90% training (10% validation) + 10% testing

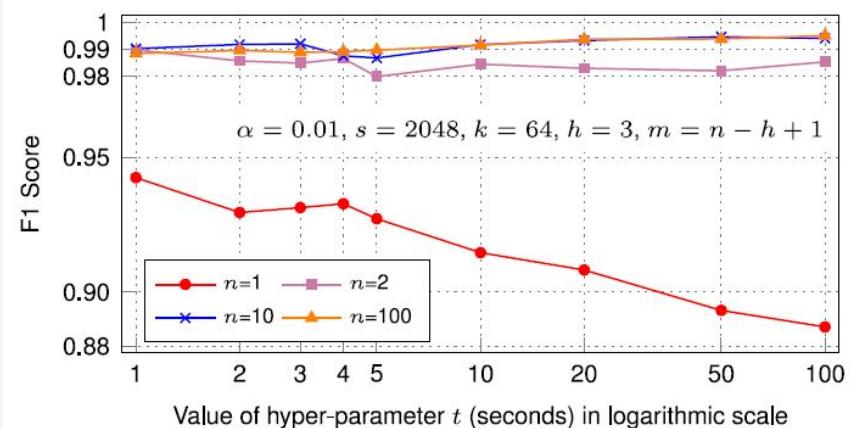
Hyper-parameter Tuning

- Grid search (using F1 score as performance metric)
- Using the validation set

Maximum number of packets/samples
 $n \geq 5$ stable



insensitive to “time window” for $n > 1$



Hyper-parameter Tuning (cont.)

- Height of convolutional filters
 - (testing) $h = 1, 2, 3, 4, 5 \rightarrow h=3$ (0.9950)
- Number of convolutional filters
 - k by powers of 2, from $k = 1$ to $k = 64$
 - steady increase in the F1 score $\rightarrow k = 64$
- Result:
 - grid search on 2835 combinations of hyperparameters
 - $n = 100, t = 100, k = 64, h = 3, m = 98, s = 2048, \alpha = 0.01$
 - Adam optimizer

Experimental Result

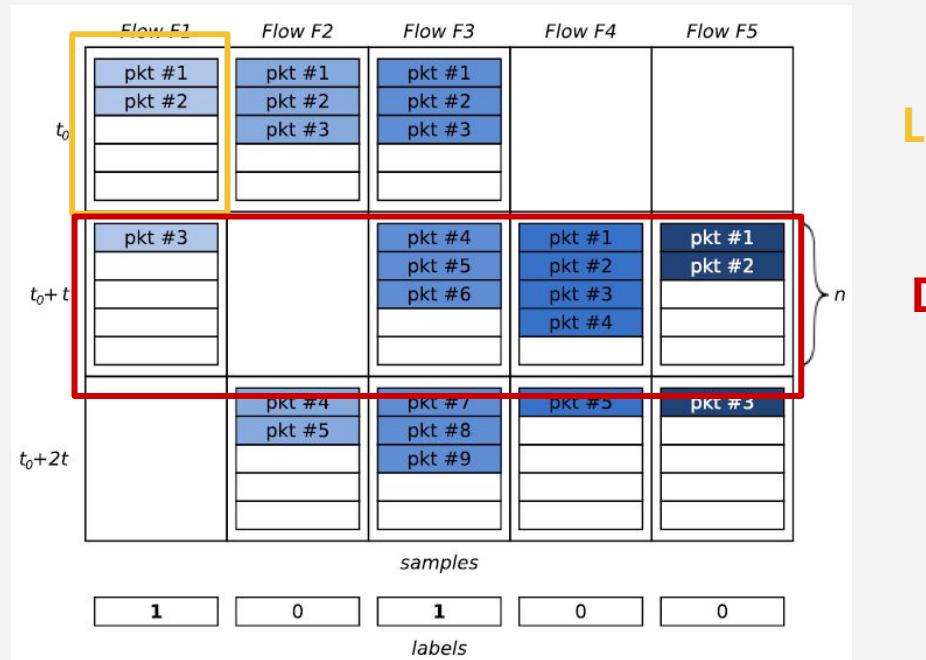
LUCID DETECTION PERFORMANCE ON THE TEST SETS

Test set	ACC	FPR	PPV	TPR	F1
ISCX2012	0.9888	0.0179	0.9827	0.9952	0.9889
CIC2017	0.9967	0.0059	0.9939	0.9994	0.9966
CSECIC2018	0.9987	0.0016	0.9984	0.9989	0.9987
UNB201X	0.9946	0.0087	0.9914	0.9979	0.9946

- LSTM ??
 - Be very difficult to train
 - Performance is inherently slower for long sequences
- data preprocessing method combined with the CNN removes the requirement to maintain temporal each whole flow.

State-of-the-Art Comparison

- DeepDefense (dataset: ISCX2012)



LUCID

DeepDefense

State-of-the-Art Comparison (cont.)

- DeepDefense - **3LSTM** (the highest score)
 - 6 LSTM layers of 64 neurons each, 2 fully connected layers of 128 neurons each, and 4 batch normalization layers
- The same architecture trains on UNB201X

Model	Trainable Parameters	ISCX 2012	CIC 2017	CSECIC 2018	UNB 201X
LUCID	2241	0.9889	0.9966	0.9987	0.9946
3LSTM	1004889	0.9880	0.9968	0.9987	0.9943

→ 3LSTM is more than 40 times slower.
LUCID is much lower computational complexity.

State-of-the-Art Comparison (con't)

PERFORMANCE COMPARISON WITH STATE-OF-THE-ART APPROACHES
USING THE ISCX2012 DATASET FOR DDoS DETECTION

Model	ACC	FPR	PPV	TPR	F1
LUCID	0.9888	0.0179	0.9827	0.9952	0.9889
DeepDefense 3LSTM [4]	0.9841	N/A	0.9834	0.9847	0.9840
TR-IDS [36]	0.9809	0.0040	N/A	0.9593	N/A
E3ML [47]	N/A	N/A	N/A	0.9474	N/A

- TR-IDS is an IDS which adopts a text-CNN to extract features from the payload of the network traffic.
- E3ML uses 20 entropy-based traffic features and three ML classifiers

State-of-the-Art Comparison (con't)

PERFORMANCE COMPARISON WITH STATE-OF-THE-ART APPROACHES
USING THE CIC2017 DATASET FOR DDoS DETECTION

Model	ACC	FPR	PPV	TPR	F1
LUCID	0.9967	0.0059	0.9939	0.9994	0.9966
DeepGFL [35]	N/A	N/A	0.7567	0.3024	0.4321
MLP [38]	0.8634	N/A	0.8847	0.8625	0.8735
1D-CNN [38]	0.9514	N/A	0.9814	0.9017	0.9399
LSTM [38]	0.9624	N/A	0.9844	0.8989	0.8959
1D-CNN + LSTM [38]	0.9716	N/A	0.9741	0.9910	0.9825

- DeepGFL is a framework designed to extract high order traffic features from low-order features forming a hierarchical graph representation.
- [38] propose four different DL models for DDoS attack detection in Internet of Things (IoT) networks.

-
-
-
-
- Kernel activations
-
-

Analysis

RANKING OF THE TOTAL COLUMN-WISE FEATURE KERNEL ACTIVATIONS FOR THE UNB201X DATASET

Feature	Total Kernel Activation	Feature	Total Kernel Activation
Highest Layer	0.69540	Time	0.11108
IP Flags	0.30337	TCP Win Size	0.09596
TCP Flags	0.19693	TCP Ack	0.00061
TCP Len	0.16874	UDP Len	0.00000
Protocols	0.14897	ICMP Type	0.00000
Pkt Len	0.14392		

- Highest Layer: highest layer links to the type of DDoS attack, e.g. network, transport, or application layer attack.
- IP Flags (16 bits): *flags Reserved Bit, Don't Fragment, More Fragments, and Fragment offset value*

"Don't Fragment" set to 1
 DDoS 99%
 Benign 92%

• • USE-CASE: DDOS DETECTION AT THE EDGE • •

- In contrast to cloud high performance servers, edge nodes cannot exploit sophisticated solutions against DDoS attacks, due to their limited computing and memory resources.

Testing

- GPU/CPU
- 1 GB RAM
- Training time

TRAINING CONVERGENCE TIME		
Setup	Time/epoch (sec)	Convergence time (sec)
LUCID Server	10.2	1880
LUCID Dev. board (GPU)	25.8	4500
LUCID Dev. board (CPU)	40.5	7450
3LSTM Dev. board (GPU)	1070	>90000



INTRODUCTION

Here you could describe the topic of the section

PRESENTATION

Here you could describe the topic of the section

ANALYSIS

Here you could describe the topic of the section

CONCLUSION

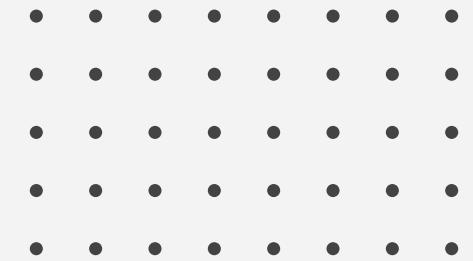
Here you could describe the topic of the section

01

02

03

04



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

—SOMEONE FAMOUS

- •
- •
- •
- •
- •

WHOA!

Here you could give a brief description of the topic you want to talk about. For example, if you want to talk about Mercury, you could say that it's the closest planet to the Sun and the smallest one in our Solar System

-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
-
-

THE SLIDE TITLE GOES HERE!

Do you know what helps you make your point clear? Lists like this one:

- They're simple
- You can organize your ideas clearly
- You'll never forget to buy milk!

And the most important thing: the audience won't miss the point of your presentation

01

NAME OF THE SECTION

You could enter a subtitle here if you need it



MAYBE YOU NEED TO DIVIDE THE TEXT



MERCURY

Mercury is the closest planet to the Sun and the smallest one in our Solar System—it's only a bit larger than our Moon

VENUS

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

-
-
-
-
-
-

Mercury is the closest planet to the Sun and the smallest one in our Solar System

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

Despite being red, Mars is actually a cold place. It's full of iron oxide dust



YOU COULD USE THREE COLUMNS, WHY NOT?

A PICTURE ALWAYS REINFORCES THE CONCEPT

If you want to replace this picture in Google Slides, select it, right-click and choose Replace image > Upload from computer. Open the file that you want and then adjust it if needed. In PowerPoint, select the picture, right-click and choose Change Picture. Open the file and adjust it



A vertical photograph of the Brooklyn Bridge's stone arches and towers, set against a bright, overexposed sky. The perspective is from a low angle looking up.

02

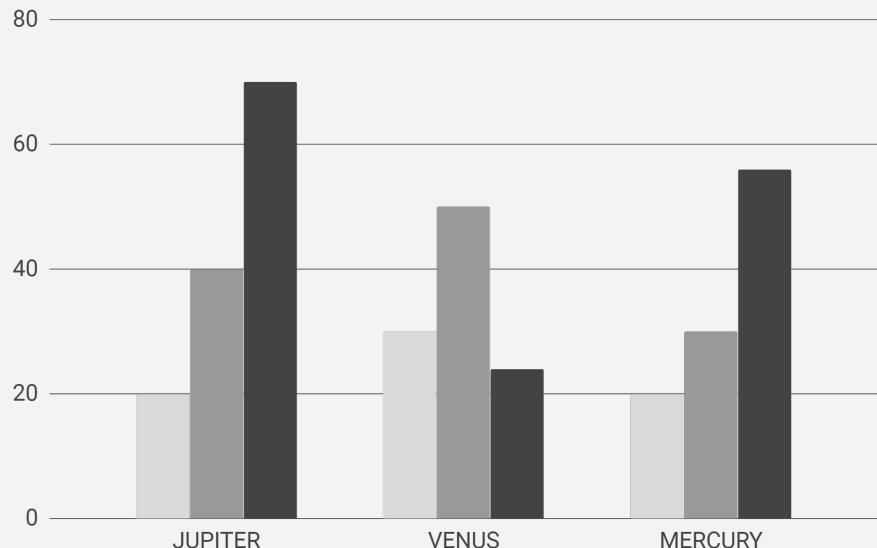
NAME OF THE SECTION

You could enter a subtitle here if you need it

A PICTURE IS WORTH A THOUSAND WORDS



IF YOU WANT TO MODIFY THIS GRAPH, CLICK ON IT, FOLLOW THE LINK, CHANGE THE DATA AND REPLACE IT

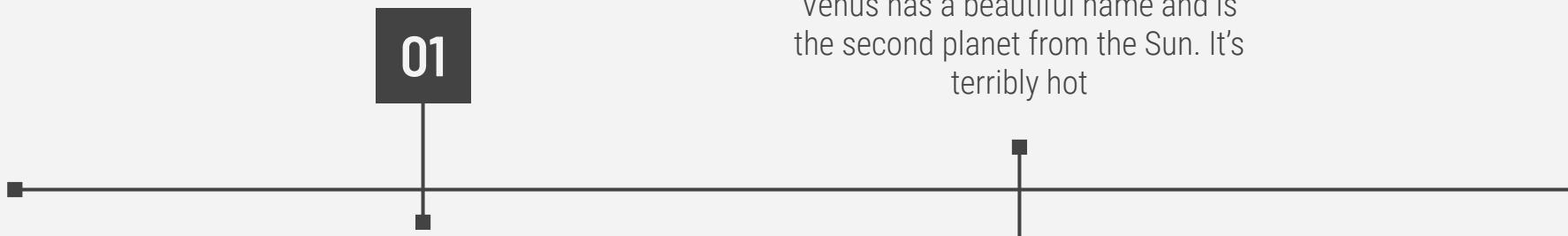


JUPITER is a gas giant and the biggest planet in our Solar System

VENUS has a beautiful name and is the second planet from the Sun

MERCURY is the smallest planet in our Solar System

A TIMELINE ALWAYS WORKS WELL



Mercury is the closest planet to the Sun and the smallest one in our Solar System

Venus has a beautiful name and is the second planet from the Sun. It's terribly hot

A TIMELINE ALWAYS WORKS WELL

Saturn is the ringed planet. It's a gas giant composed mostly of hydrogen and helium

03

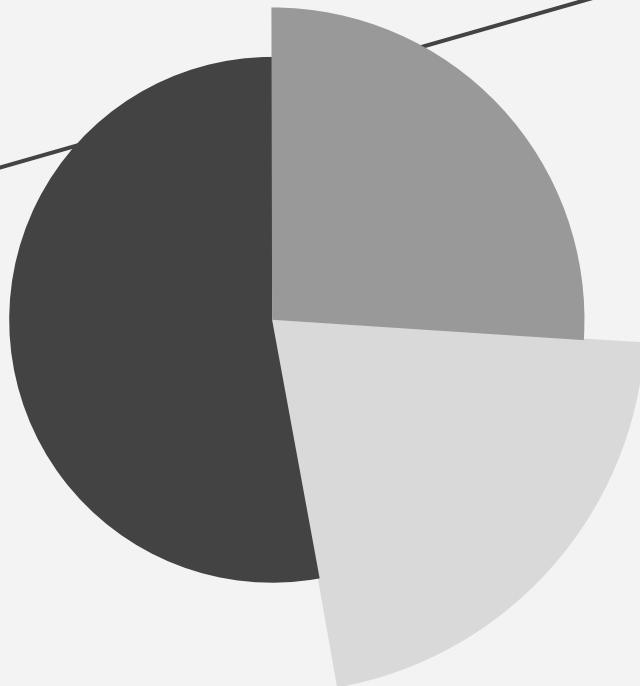
04

Neptune is the farthest planet from the Sun and the fourth-largest by diameter in our Solar System



**AWESOME
WORDS**

THIS IS A GRAPH



Mercury is the closest planet to the Sun
and the smallest one in our Solar System



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



Despite being red, Mars is actually a cold
place. It's full of iron oxide dust



... AND THE SAME GOES FOR TABLES

	2010	2015	2020
MERCURY	3,000,000	4,000,000	5,000,000
VENUS	1,500,000	2,000,000	2,500,000

HOW ABOUT THESE PERCENTAGES?



45%

Neptune is the farthest planet from the Sun

22%

Mercury is the closest planet to the Sun

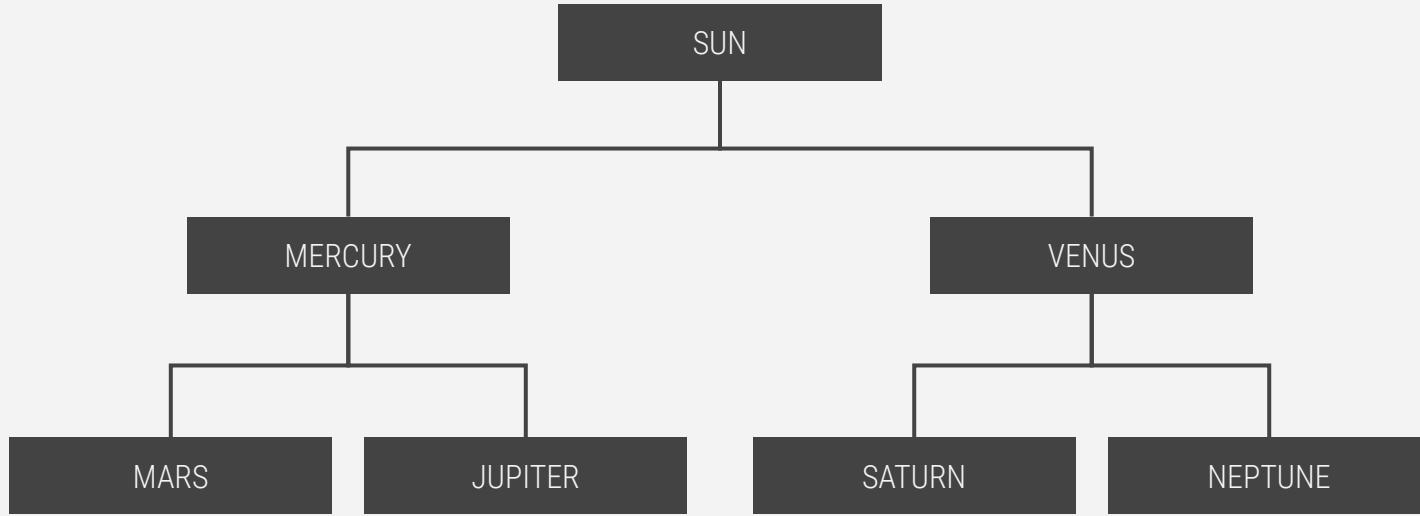
33%

Despite being red, Mars is actually a cold place

44,000,000

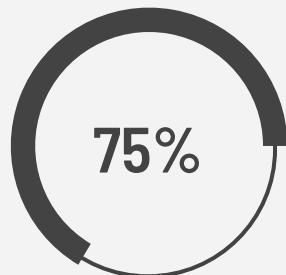
Mercury is the closest planet to the Sun and the smallest of them all

DON'T FORGET WHAT'S IMPORTANT



DO YOU PREFER THESE OTHER PERCENTAGES?

Venus has a beautiful name



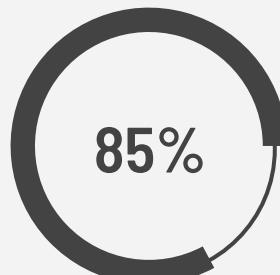
2010

Neptune is the farthest planet from the Sun



2015

Mercury is the closest planet to the Sun



2020

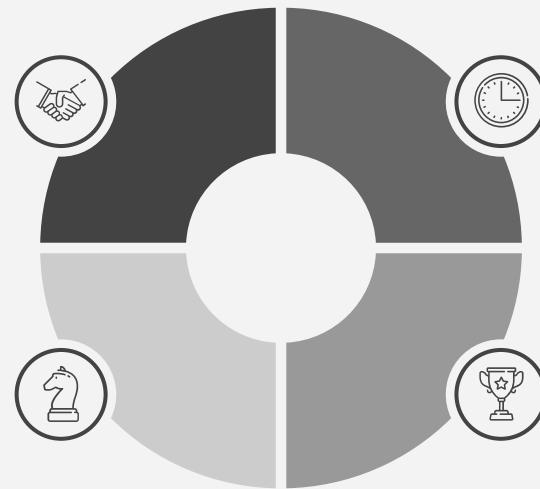
REINFORCE THE CONCEPTS USING INFOGRAPHICS!

MARS

Despite being red, Mars is actually a cold place

JUPITER

It's a gas giant and the biggest planet in our Solar System



VENUS

Venus has a beautiful name and is the second planet

MERCURY

Mercury is the smallest planet in our Solar System

SOMETIMES, REVIEWING CONCEPTS IS A GOOD IDEA

01

Despite being red, Mars is actually a cold place

02

Mercury is the smallest planet in our Solar System

03

Saturn is a gas giant, composed mostly of hydrogen and helium

04

Venus has a beautiful name, but it's very hot

05

Neptune is the farthest planet from the Sun

06

Jupiter is the biggest planet in our Solar System

OUR SERVICES

\$0

You can explain your
product or your service

Characteristic
Characteristic

FREE

\$35

You can explain your
product or your service

Characteristic
Characteristic

PREMIUM



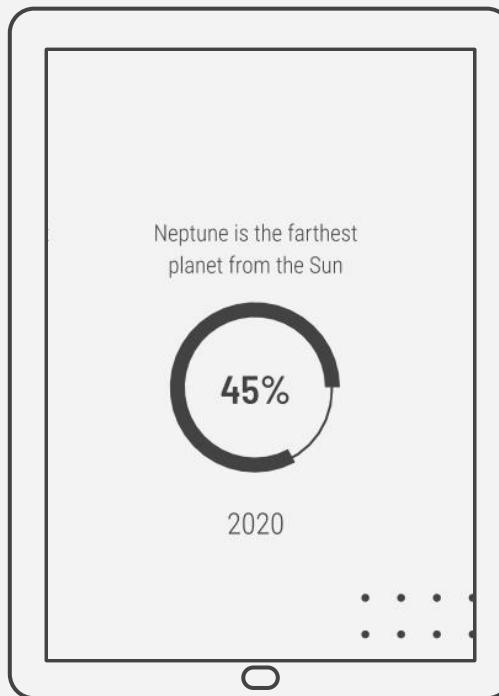
03

NAME OF THE SECTION

You could enter a subtitle here if you need it

TABLET APP

You can replace the image on the screen with your own work. Just delete this one, add yours and send it to the back



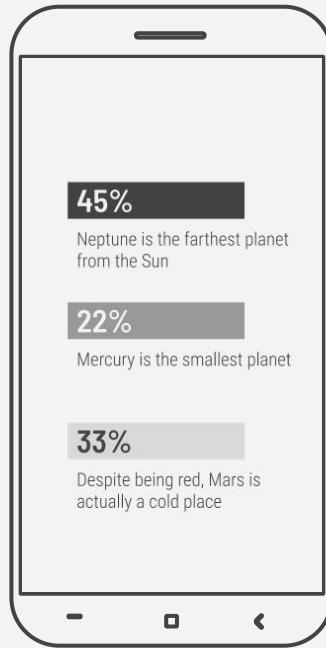


DESKTOP SOFTWARE

You can replace the image on the screen with your own work. Just delete this one, add yours and send it to the back

MOBILE WEB

You can replace the image on the screen with your own work. Just delete this one, add yours and send it to the back



OUR TEAM

SAMMY PATTERSON, 40

You can replace the image on the screen with
your own

JENNA DOE, 32

You can replace the image on the screen with
your own



THANKS!



Do you have any questions?

youremail@freepik.com
+91 620 421 838
yourcompany.com

CREDITS: This presentation template was created by [Slidesgo](#),
including icons by [Flaticon](#), and infographics & images by [Freepik](#)

Please keep this slide for attribution

ALTERNATIVE RESOURCES

PHOTOS

- High angle view of player throwing basketball in the hoop
- Group of people holding their hands up
- Girl catching a ball helped by her team mates
- Young businessman holding coffee cup in hand looking at buildings in the city
- Group of young businesspeople analyzing graph over wooden desk

RESOURCES

PHOTOS

- City skyline and bridge with us flag
- Crop female keeping baseball and glove
- Brooklyn bridge and skyscrapers on skyline
- Front view women working together
- Rear view of a young man practicing basketball

Instructions for use

In order to use this template, you must credit **Slidesgo** by keeping the **Thanks** slide.

You are allowed to:

- Modify this template.
- Use it for both personal and commercial projects.

You are not allowed to:

- Sublicense, sell or rent any of Slidesgo Content (or a modified version of Slidesgo Content).
- Distribute Slidesgo Content unless it has been expressly authorized by Slidesgo.
- Include Slidesgo Content in an online or offline database or file.
- Offer Slidesgo templates (or modified versions of Slidesgo templates) for download.
- Acquire the copyright of Slidesgo Content.

For more information about editing slides, please read our FAQs or visit Slidesgo School:

<https://slidesgo.com/faqs> and <https://slidesgo.com/slidesgo-school>

Fonts & colors used

This presentation has been made using the following fonts:

Barlow Semi Condensed

(<https://fonts.google.com/specimen/Barlow+Semi+Condensed>)

Roboto Condensed

(<https://fonts.google.com/specimen/Roboto+Condensed>)

#434343

#666666

#999999

#cccccc

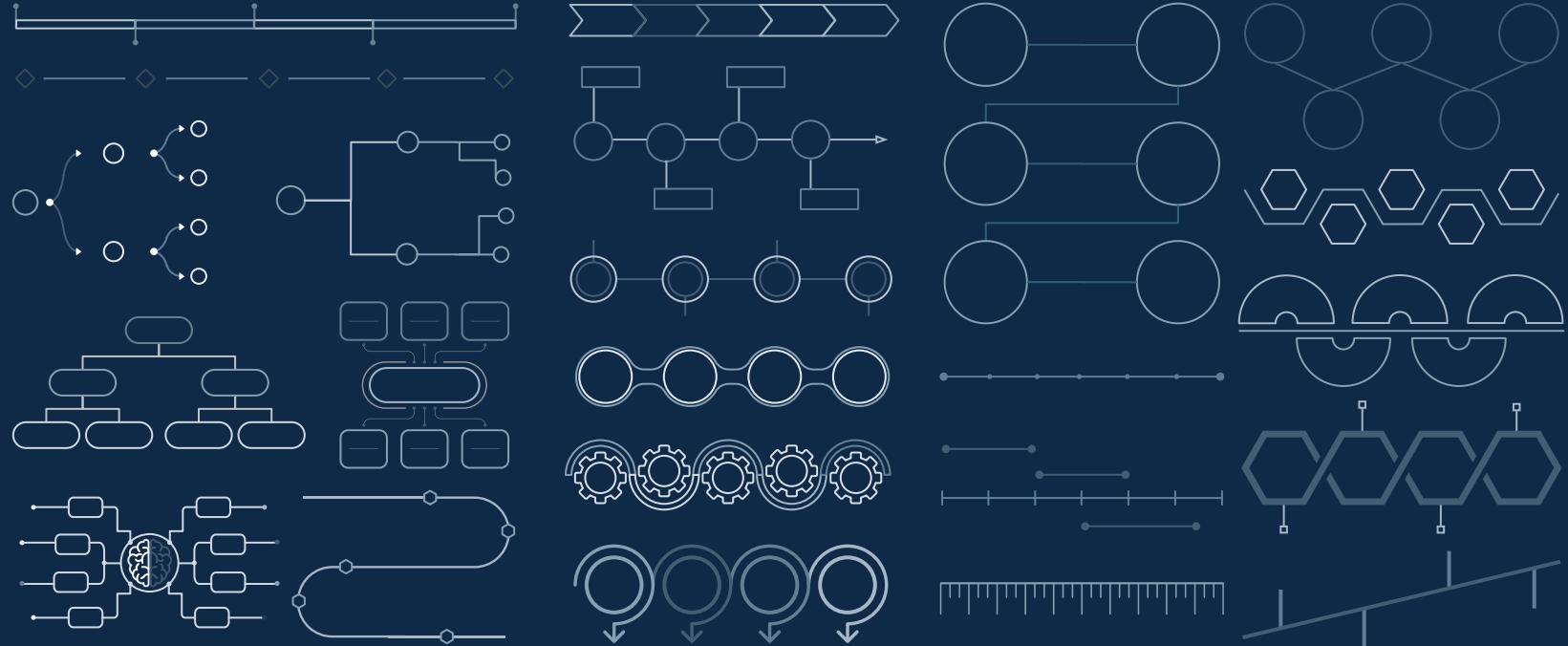
#f3f3f3

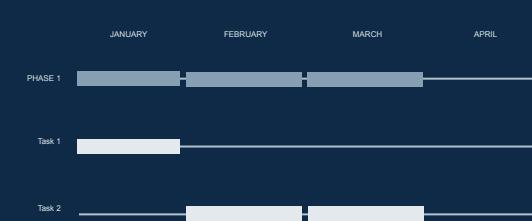
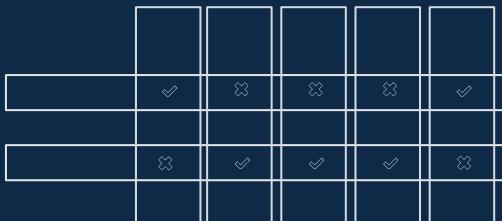
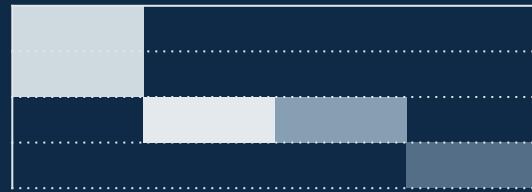
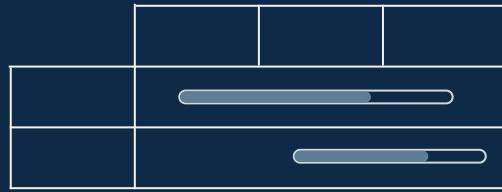
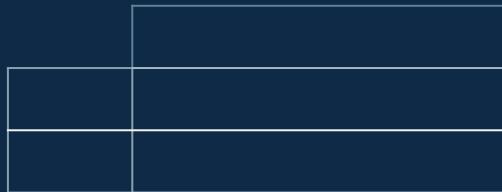
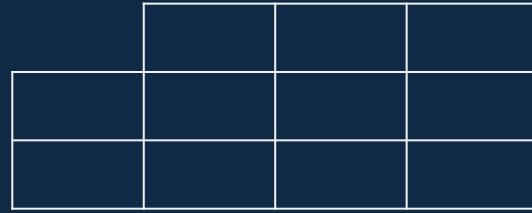
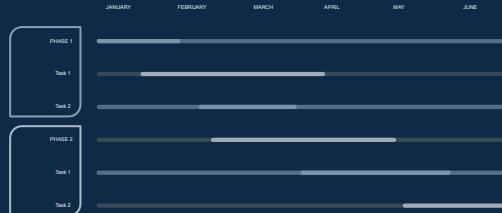
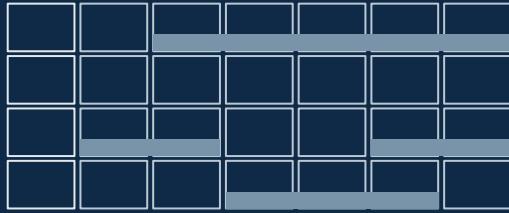
Use our editable graphic resources...

You can easily resize these resources, keeping the quality. To change the color, just ungroup the resource and click on the object you want to change. Then, click on the paint bucket and select the color you want. Don't forget to group the resource again when you're done.

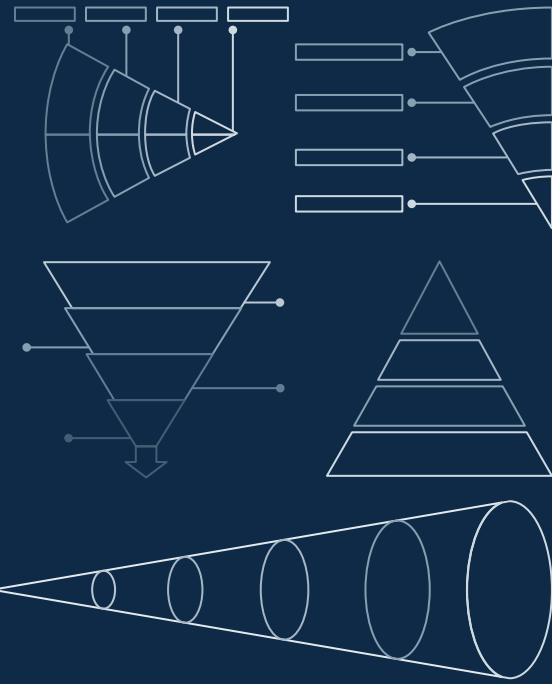
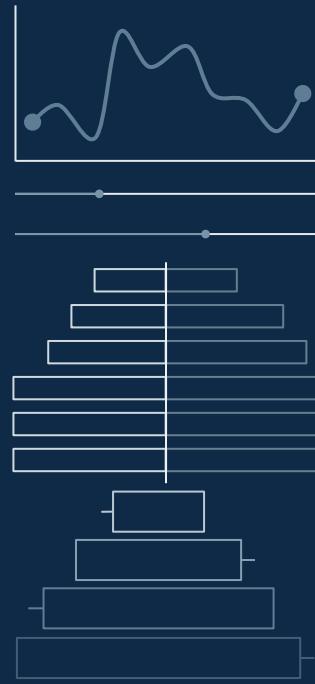
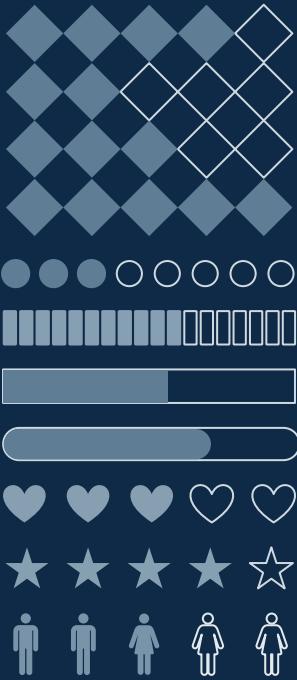
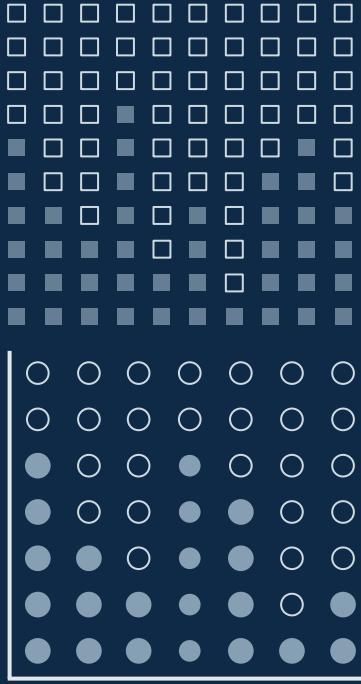












...and our sets of editable icons

You can resize these icons, keeping the quality.

You can change the stroke and fill color; just select the icon and click on the paint bucket/pen.

In Google Slides, you can also use Flaticon's extension, allowing you to customize and add even more icons.



Educational Icons



Medical Icons



Business Icons



Teamwork Icons



Help & Support Icons



Avatar Icons



Creative Process Icons



Performing Arts Icons



Nature Icons



SEO & Marketing Icons



