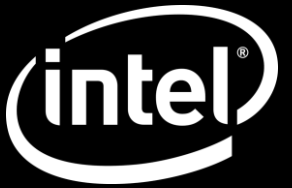
JARVIS NEVER SAW IT COMING

Hacking machine learning (ML) in speech, text and face recognition – and frankly, everywhere else

LEGAL NOTICES AND DISCLAIMERS



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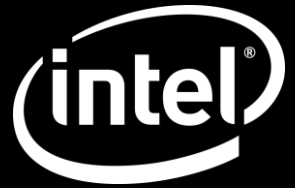
No Horses, Flamingos, Hedgehogs, Turtles or sentient* AI models were harmed during the making of this presentation

* We hope

$ ID



Guy Barnhart-Magen

@barnhartguy

BSidesTLV Co-founder and CTF Lead

Ezra Caltum

@acaltum

BSidesTLV Co-Founder

DC9723 Lead

BUILDING ON THE SHOULDERS OF GIANTS

https://www.deviantart.com/callyste/art/Rocket-Raccoon-and-Groot-485953724

HOW DID WE GET HERE?

Awesome Conversations ➔ Ideas

WHAT CAN YOU EXPECT?

What are we going to talk about

WHAT CAN YOU EXPECT?

What are we going to talk about

What you should be paying attention to

WHAT CAN YOU EXPECT?

What are we going to talk about

What you should be paying attention to

What we are not going to talk about

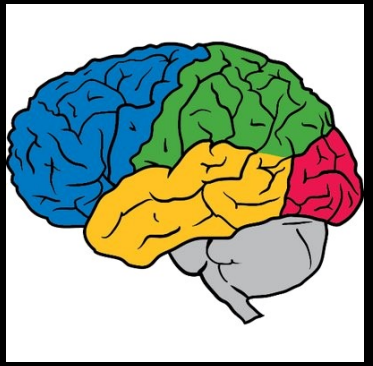
CLEVER HANS

https://github.com/tensorflow/cleverhans

https://upload.wikimedia.org/wikipedia/commons/e/e3/CleverHans.jpg

“We have reached the point where machine learning works, but may easily be broken”

Nicolas Papernot, Google PhD Fellow in Security
Ian Goodfellow, Research scientist at Google Brain



http://www.cleverhans.io/security/privacy/ml/2016/12/15/breaking-things-is-easy.html
https://pbs.twimg.com/profile_images/799327801388077057/HcDnA1H7_400x400.jpg

SOME BACKGROUND

ARTIFICIAL INTELLIGENCE?

Machine Learning

Study many images labeled as flamingo
Identify the flamingo in the image

https://upload.wikimedia.org/wikipedia/commons/b/ba/Alice_par_John_Tenniel_30.png

ARTIFICIAL INTELLIGENCE?

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- Study many images labeled as flamingo
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Deep Learning

- Study many images
- Identify the flamingo, hedgehog, etc.

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ARTIFICIAL INTELLIGENCE?

Machine Learning

- Study many images labeled as flamingo
- Identify the flamingo in the image

Deep Learning

- Study many images
- Identify the flamingo, hedgehog, etc.

Artificial Intelligence

- Is she hugging the flamingo, or playing cricket?
- Is she happy, sad?

https://upload.wikimedia.org/wikipedia/commons/b/ba/Alice_par_John_Tenniel_30.png

EVERYBODY EXCHANGES "AI" AND "ML"

So do I

Sorry

“INTELLIGENT” SYSTEM

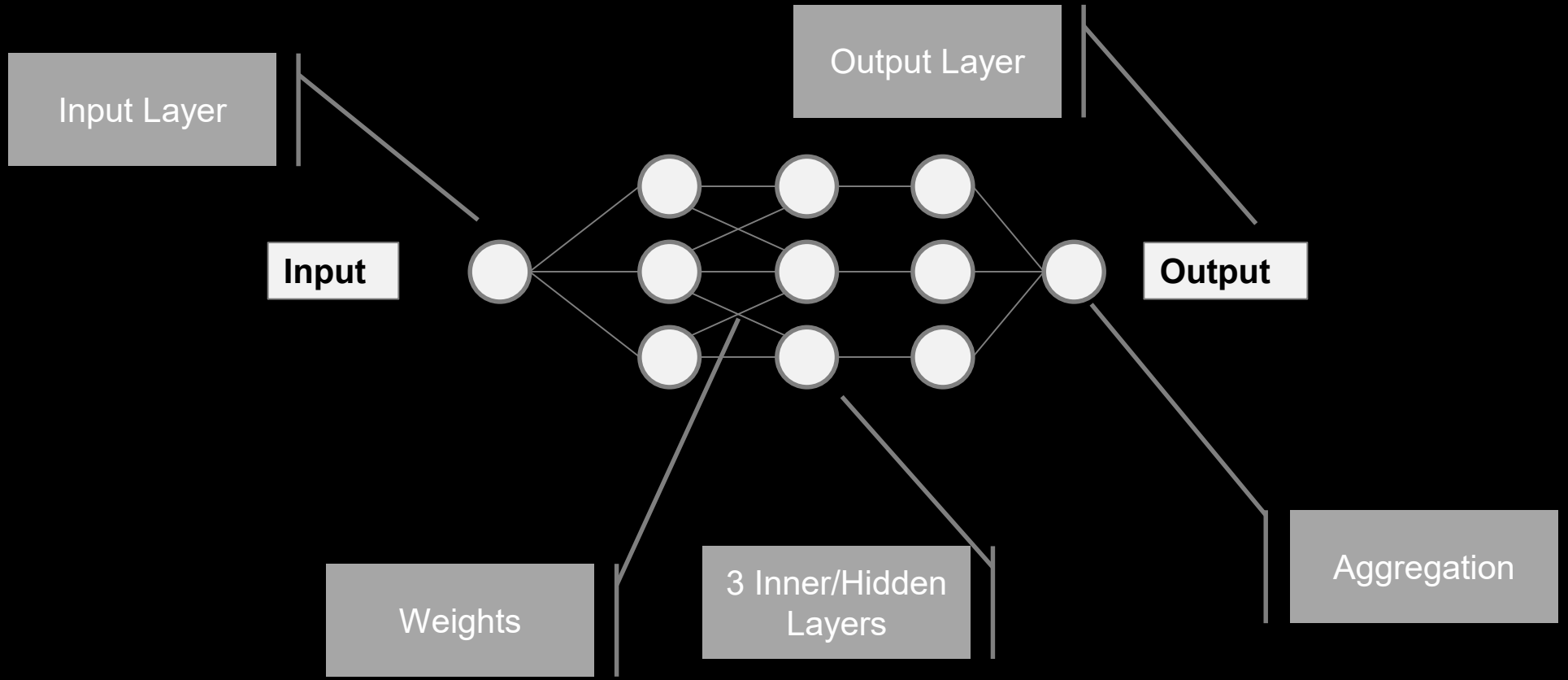
Most AI systems were designed to **solve a specific problem**, well.

https://www.reactiongifs.us/wp-content/uploads/2015/02/do_the_robot_futurama.gif

MACHINE LEARNING 101


SIT BACK 'N RELAX
WE GOT THIS
imgflip.com

WHAT IS A ML MODEL?



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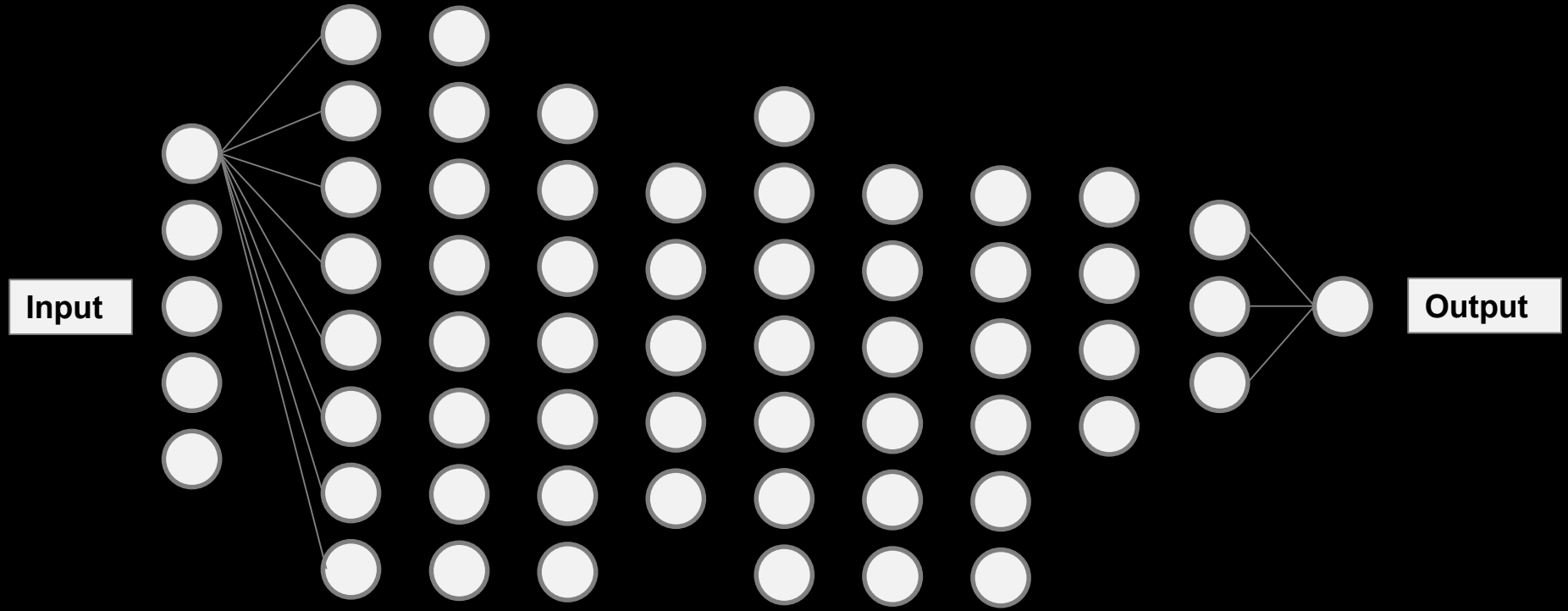

WHAT IS A ML MODEL?

- Training: Iterative process to adjust weights
- The “model” includes:
  - Topology/Layout
  - Weights/Parameters
  - Functions
- This is the real IP (Intellectual Property) in the system!

NOW SERIOUSLY

- When multiplying one matrix with another, you get a new matrix

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- The values are the product of the rows and columns of these matrices

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- When multiplying one matrix with another, you get a new matrix
- The values are the product of the rows and columns of these matrices
- A vector is a single dimensioned matrix, so an array is a vector, and a matrix is a two dimensional array

CODE POINT OF VIEW

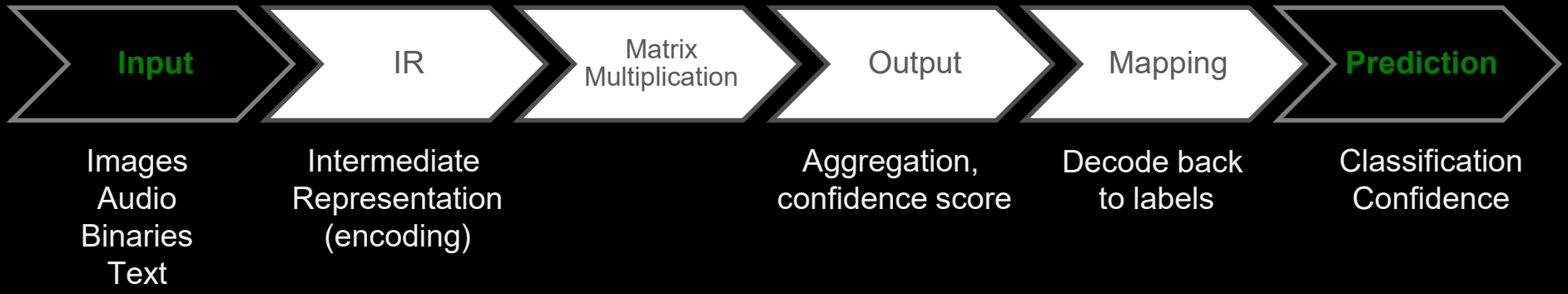
```
int16 vector = [];

struct weights {
     int rows;
     int cols;
     double **data;
};
```

TOO MUCH VOODOO!

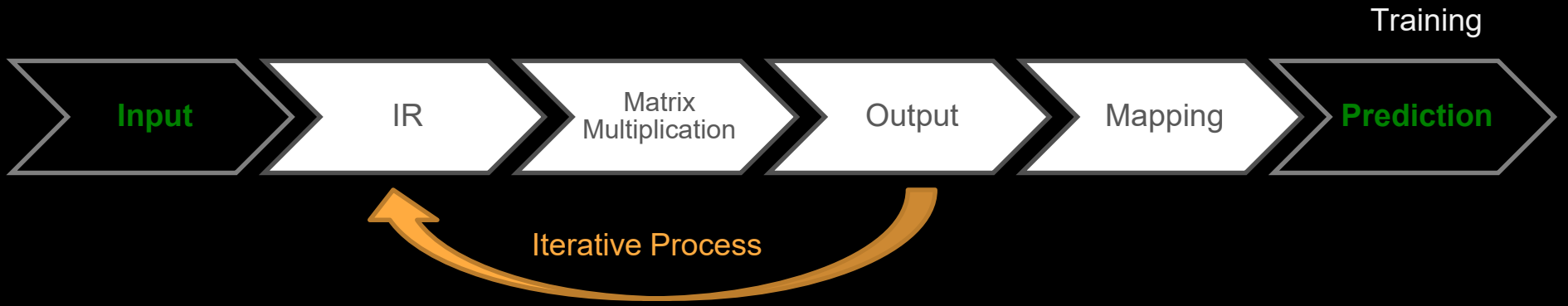
Images
Audio
Binaries
Text

Classification
Confidence

NOT TOO MUCH VOODOO!



FROM TRAINING TO INFERENCE



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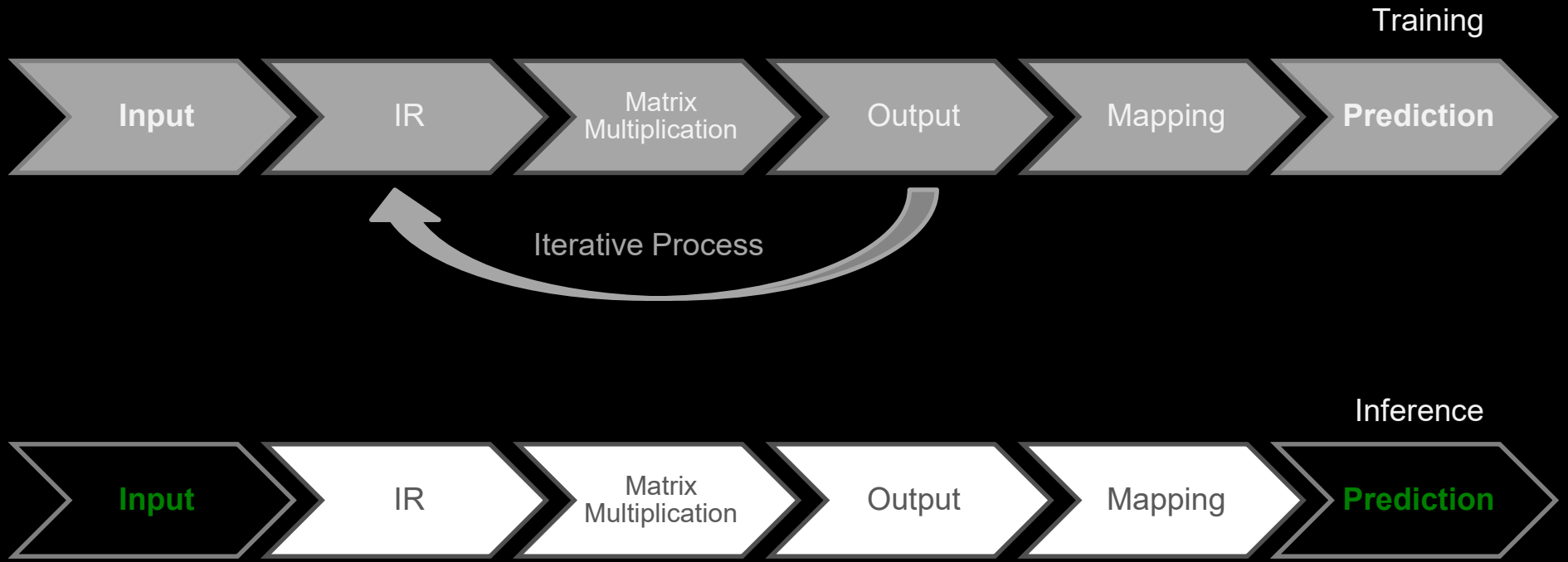


MODEL != CODE

EXECUTABLE

Code execution flow

ML MODEL

Math operations, transition functions

EXECUTABLE

Code execution flow

Data Structures

ML MODEL

Math operations, transition functions

Intermediate Representation

EXECUTABLE

Code execution flow

Data Structures

Code Review or Reverse Engineering

ML MODEL

Math operations, transition functions

Intermediate Representation

Model structure (Black Magic)

$ HEXDUMP /MODELS/RESNET

```
00000000   0A 09 52 65  73 4E 65 74  2D 35 30 1A  04 64 61 74  61 A2 06 C9  ..ResNet-50..data...
00000014   A8 02 0A 05  63 6F 6E 76  31 12 0B 43  6F 6E 76 6F  6C 75 74 69  ....conv1..Convoluti
00000028   6F 6E 1A 04  64 61 74 61  22 05 63 6F  6E 76 31 3A  8C A6 02 2A  on..data".conv1:...*
0000003C   80 A6 02 0E  72 E7 3C 64  FD 94 3C 1E  21 82 3C BE  99 1E 3B 99  ....r.<d..<.!.<...;.
00000050   26 59 BD 30  F8 41 BD 63  E7 97 3C E1  E8 02 3C 07  DD CB 3C 86  &Y.0.A.c..<...<...<.
00000064   22 9D 3D 7B  DC B8 3D E1  F3 9A BC 7F  85 A2 BD BB  AF 7B BC A9  ".={..=.........{..
00000078   0F E1 BC C7  A9 86 BD 8E  C6 A3 3C 9F  32 3D 3E 3D  9A EC 3D A2  ..........<.2=>=..=.
0000008C   47 B8 BD 7F  D5 C1 BD 62  5C 20 BC 30  47 A2 BD 68  EF 04 BE EA  G......b\ .0G..h....
000000A0   0A C3 3D C3  46 8A 3E 08  96 CB 3D 9D  A3 74 BC F8  E4 BD 3C 11  ..=.F.>...=..t....<.
000000B4   44 3E BD 16  66 3B BE 5B  C9 1F BE 30  9D 5B 3D C4  FF AA 3D DB  D>..f;.[...0.[=...=.
000000C8   60 17 3D 60  13 2D 3D FC  32 3C 3D 9B  F0 3E BD FA  16 02 BE 5A  `.=`.-=.2<=..>.....Z
000000DC   3A AC BC FB  13 08 3D 75  3A CD 3C FE  B3 6F 3C A5  4D 10 3D 95  :.....=u:.<..o<.M.=.
000000F0   A2 86 3B 58  56 77 BD 7C  A6 8C BC 49  A6 3C 3C C3  01 9D 3B AF  ..;XVw.|...I.<<...;.
00000104   4A C0 3B FD  A4 99 3C C7  09 14 3D 82  88 8C 3C 48  9B BF BD 30  J.;...<...=...<H...0
00000118   28 FE BD 3E  9C DB BC 2B  EB FB BB B4  09 C7 3C 0C  08 19 3E 64  (..>...+......<...>d
0000012C   CC 5C 3E E5  5C 5B 3C 02  1E 35 BE B7  CB FB BD 9A  E7 98 BD 64  .\>.\[<..5.........d
00000140   27 1C BE 8F  F4 79 3D B1  7A D4 3E BF  27 AA 3E 62  ED A6 BD 9B  '....y=.z.>.'.>b....
00000154   2D 58 BE 6C  01 5F BD 2A  B5 82 BE 52  63 87 BE 02  63 57 3E 1F  -X.l._.*...Rc...cW>.
00000168   F5 11 3F 8D  F2 8D 3E 0A  EF D8 BC E1  D0 BC 3C 15  1F 36 BE 3F  ..?...>.......<..6.?
0000017C   D5 D2 BE DC  72 89 BE 71  40 3E 3E D3  48 80 3E FD  5D C5 3D 9A  ....r..q@>>.H.>.].=.
00000190   17 C8 3D 51  88 1F 3D C4  F3 44 BE 7D  A0 95 BE 1E  C7 18 BD F1  ..=Q..=..D.}........
000001A4   E8 CB 3D D8  3F CD 3D FE  C2 7A 3D DB  EE 81 3D C8  CE B6 BC 3E  ..=.?.=..z=...=....>
000001B8   95 2E BE 76  BF B0 BD FE  14 F3 3B 27  70 E1 3C A2  F7 1F BB 10  ...v......;'p.<.....
000001CC   05 9C 3C 7C  8D B2 3C 08  93 5D BB AA  9C 9D BD AA  0B 92 BD 22  ..<|..<..]..........."
---   ResNet-50-model.caffemodel        --0x1DF/0x61B73BD-------------------------------------
```

FUN FACTS!

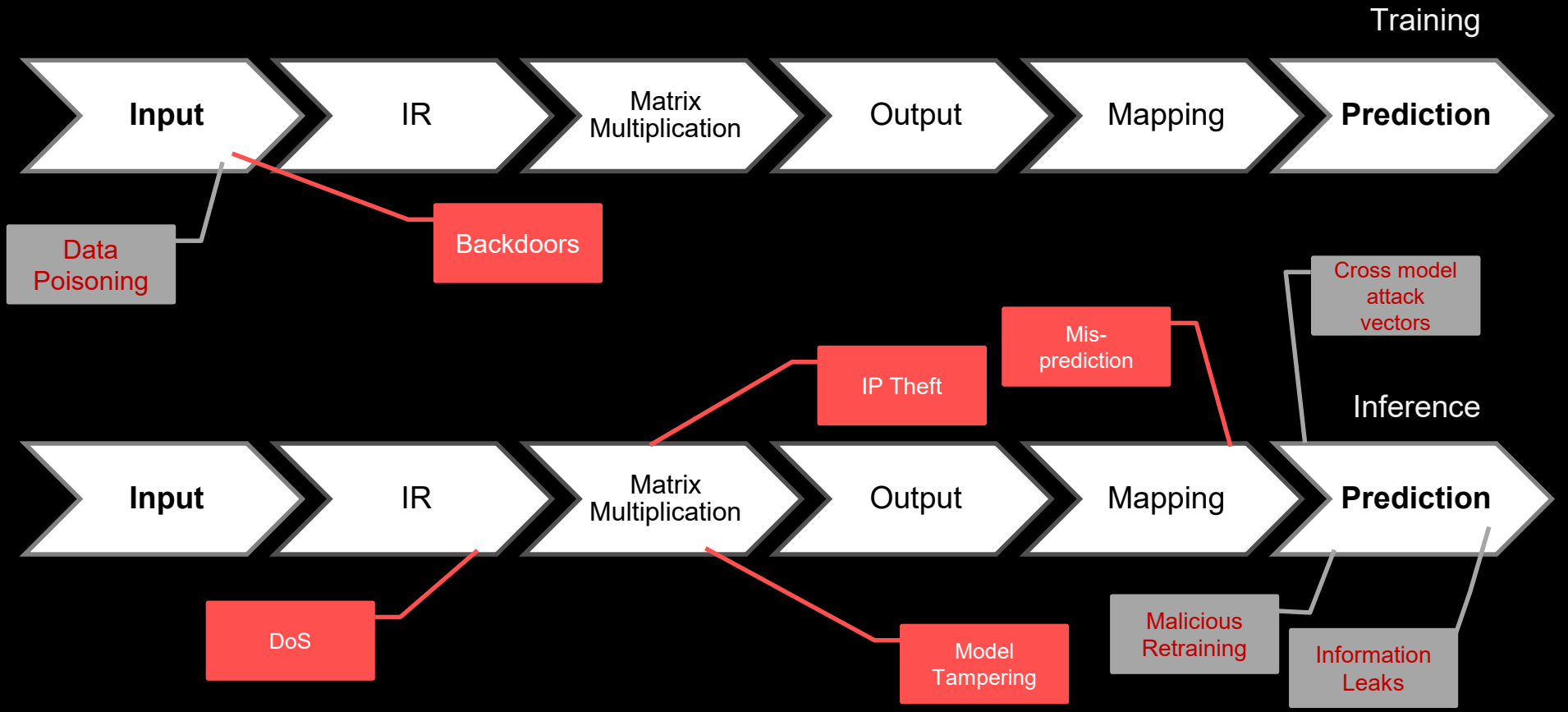
The algorithm is designed to optimize for the “strongest signal”

The model (matrices) can be GB in size

Bias is a part of the system learning process

BIAS - SOLVING THE WRONG PROBLEM

FROM TRAINING TO INFERENCE



SCORING

We used the CVSS 3.0 scoring, and ordered by business impact

TOP 5 ATTACKS (CVSS)

1	DoS	7.5 (High)
2	Misprediction (adversarial attacks)	7.5 (High)
3	Model Tampering	7.4 (High)
4	IP Theft	5.9 (Medium)
5	Backdoors	3.9 (Low)

TOP 5 ATTACKS (BUSINESS IMPACT)

1	IP Theft	5.9 (Medium)
2	Model Tampering	7.4 (High)
3	DoS	7.5 (High)
4	Backdoors	3.9 (Low)
5	Misprediction (Adversarial attacks)	7.5 (High)

HOW TO BUILD AN ATTACK

What do you need to know?

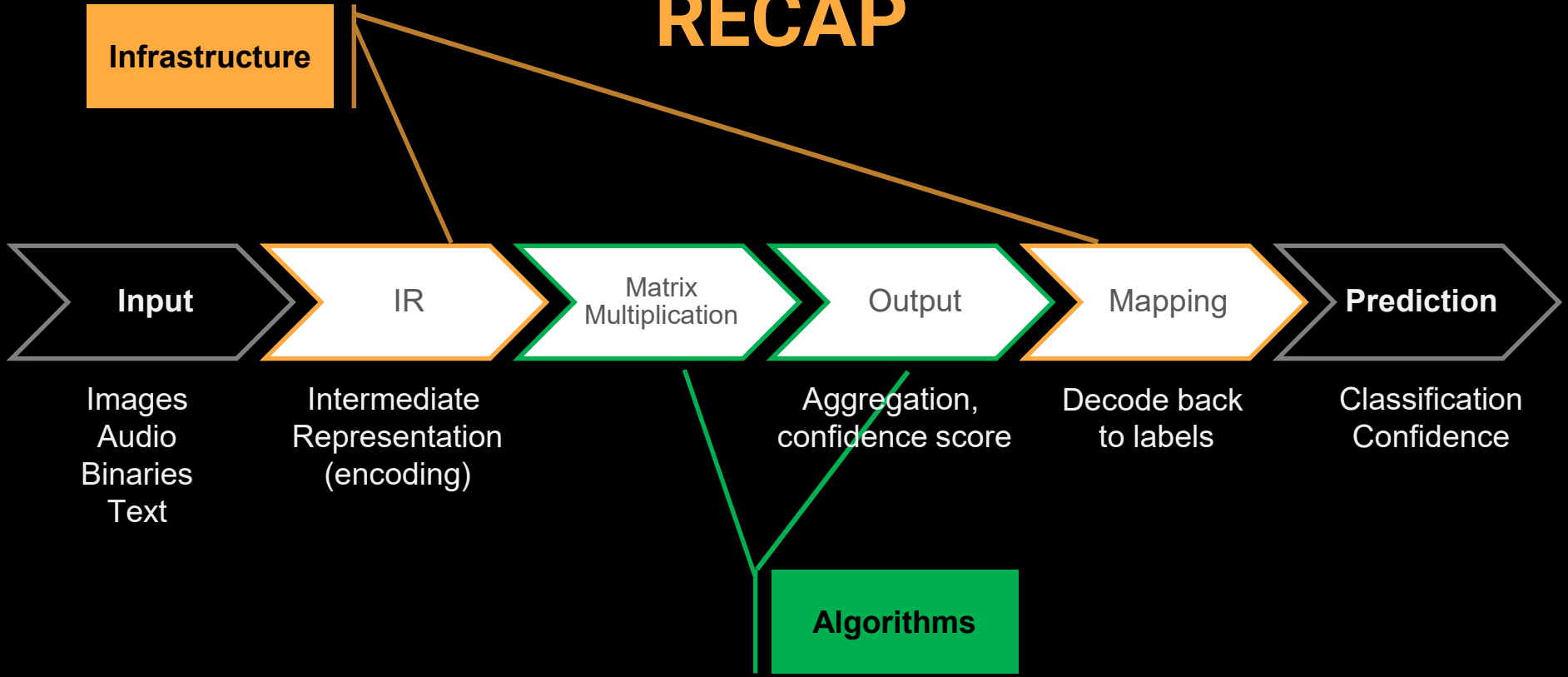
What areas should you target?

What do you need to have access to?

WHERE TO ATTACK?

You can either go after the system infrastructure, or the algorithms

RECAP


Infrastructure
Input
IR
Matrix Multiplication
Output
Mapping
Prediction
Images
Audio
Binaries
Text
Intermediate Representation (encoding)
Aggregation, confidence score
Decode back to labels
Classification Confidence
Algorithms

PARSING

ML needs to convert the input into a matrix

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Parsing is hard

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AI developers don’t develop file formats. Or parsers.

PARSING

ML needs to convert the input into a matrix

Parsing is hard

AI developers don’t develop file formats. Or parsers.

The common solution is to just bring the dependency into the project

DEPENDENCIES

So – they are bringing outside libraries into their stack

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And bringing with them a common problem – supply chain and patch management

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A common framework, must support multiple file formats…

So let's fuzz the file format parsing

WE FAILED MISERABLY AT THE BEGINNING

We were fuzzing on a pretty large compute cluster, but we had terrible performance!

FUZZING

What to focus on?	Why focus here?	Issues?
Caffe	Full coverage	Extremely slow

FUZZING

What to focus on?	Why focus here?	Issues?
Caffe	Full coverage	Extremely slow
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FUZZING

What to focus on?	Why focus here?	Issues?
Caffe	Full coverage	Extremely slow
OpenCV	Limited coverage	Medium speed
LibXXX	Very fast	Unknown code paths
Upstream	Fuzzing not needed	Patched? Workable?

WE FAILED MISERABLY AT THE BEGINNING

We used a RAM disk to accelerate access

And then used the same cluster for a different research, and rebooted

We also forgot to turn off the logging

which lead to a system crash

which lead to loosing some valid crashes

FACE PALM

Scaling exploitation is hard (DevOps?)

EVENTUALLY WE GOT OUR GRIP

PRELIMINARY RESULTS

Almost every exploit category was discovered

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Bug collisions

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Bug collisions

So many crashes

PRELIMINARY RESULTS

Almost every exploit category was discovered

Bug collisions

So many crashes

We were like children in a candy store

INITIAL EXPLOITATION

We focused on crashes in the BMP file format

Mostly – because it’s pretty easy to manually craft

SO...

FUZZING → CRASH, NOW WHAT?

1	IP Theft	5.9 (Medium)
2	Model Tampering	7.4 (High)
3	DoS	7.5 (High)
4	Backdoors	3.9 (Low)
5	Misprediction (Adversarial attacks)	7.5 (High)

Is Remote Code Execution (RCE) king?

POST EXPLOITATION

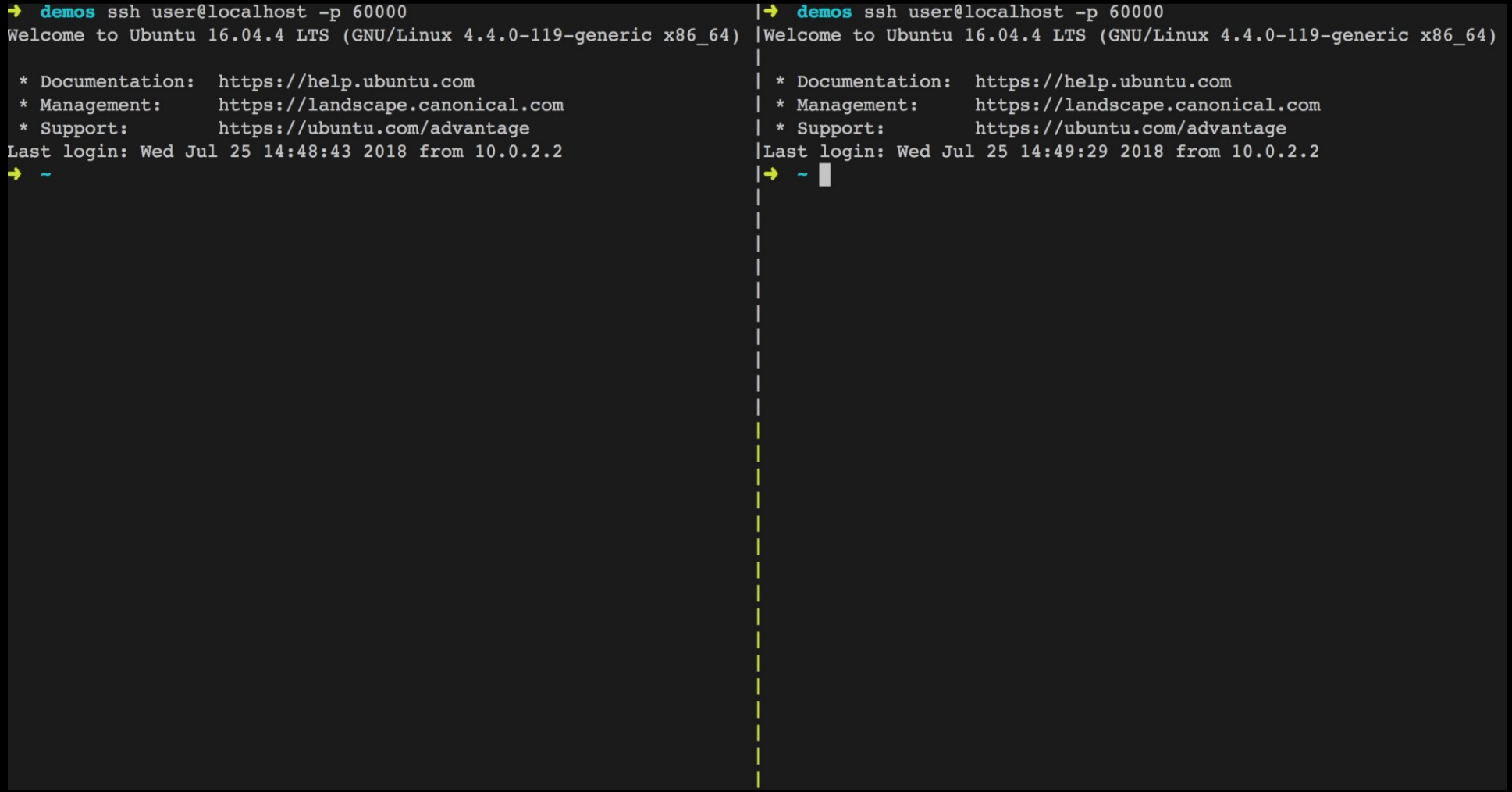
Let’s demonstrate the TOP 5

Input: Image file (~10K)

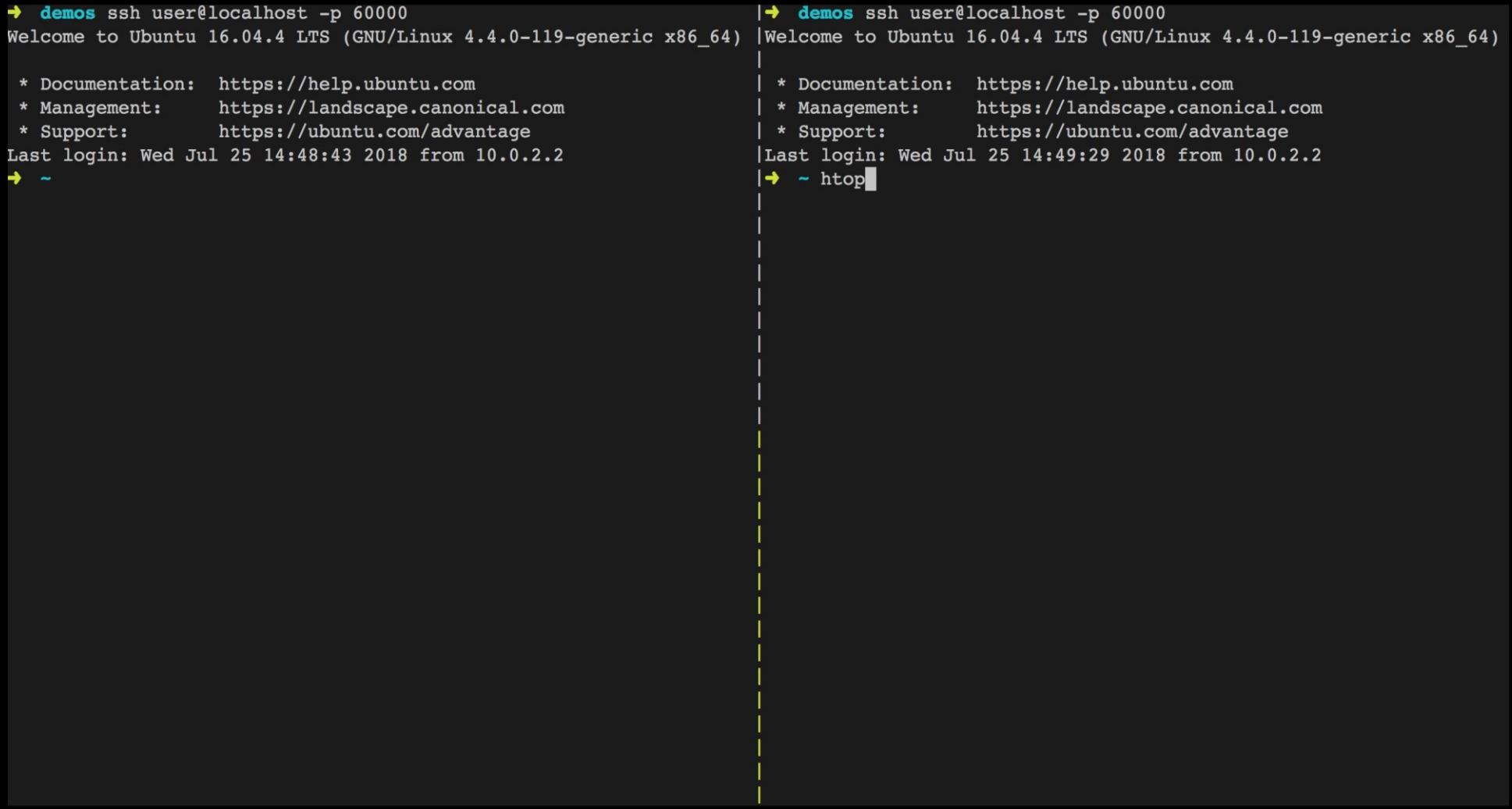
Output: Label (string)

DEMO TIME

Denial of Service



@barnhartguy @acaltum



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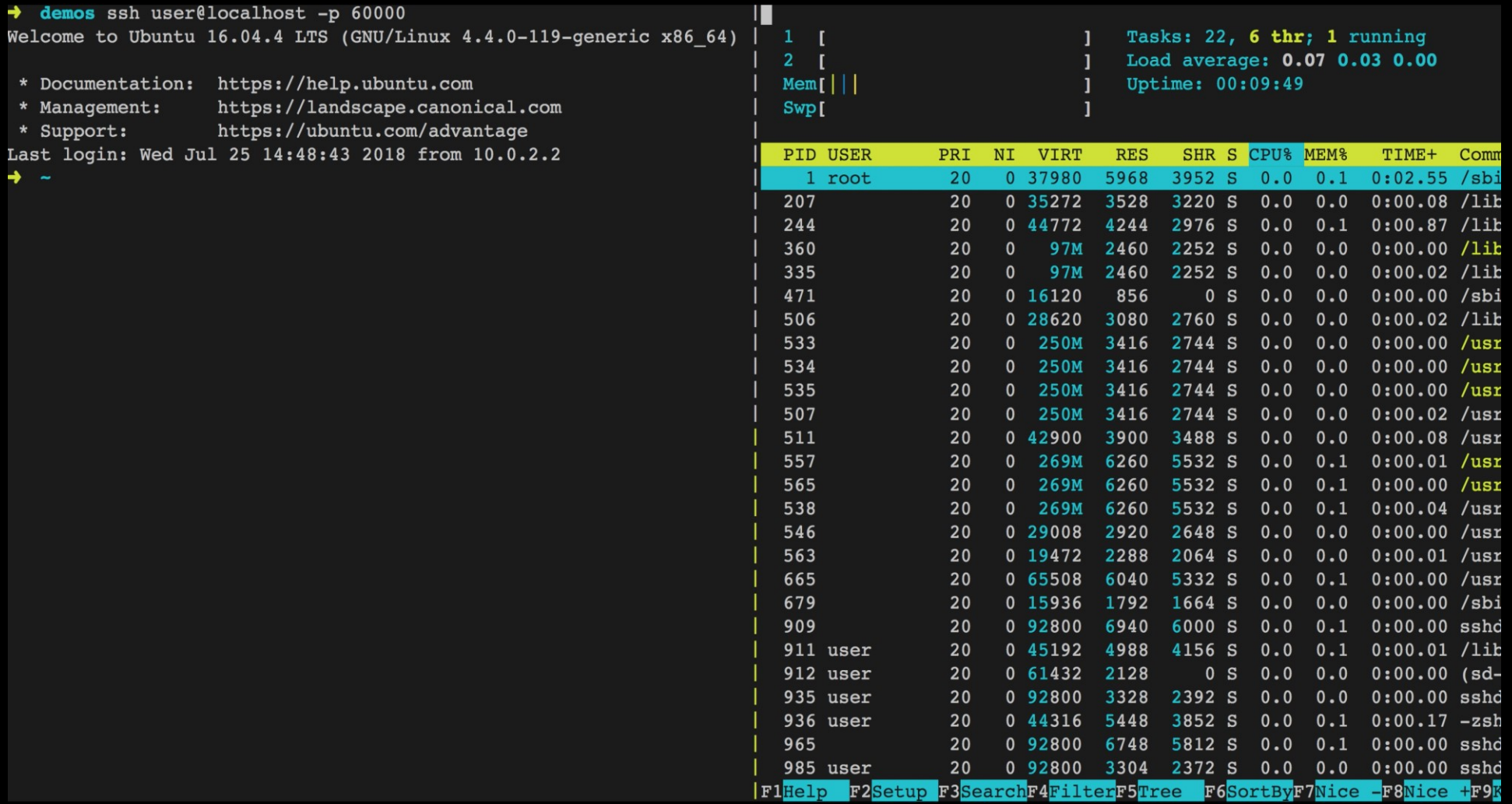

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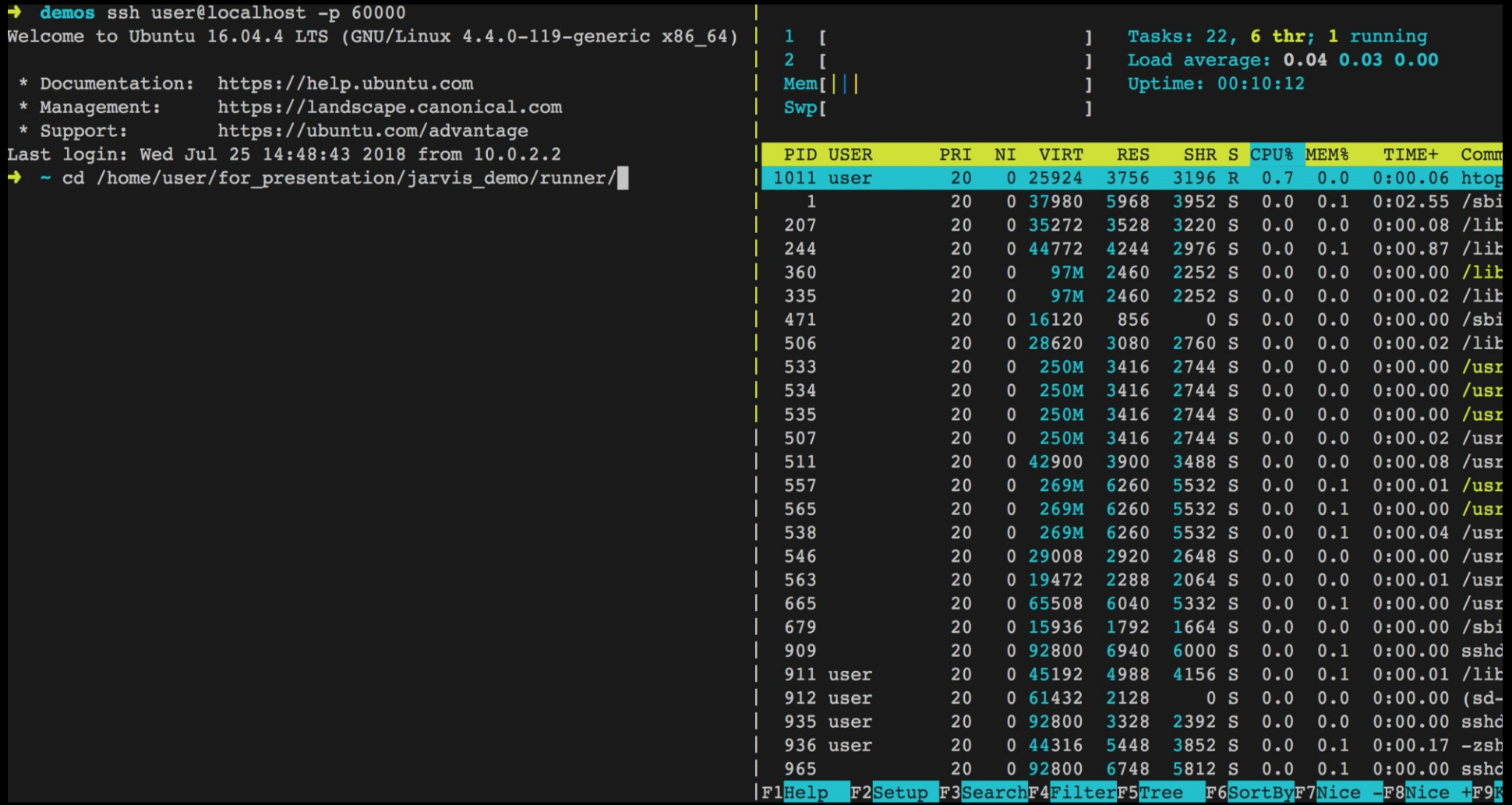

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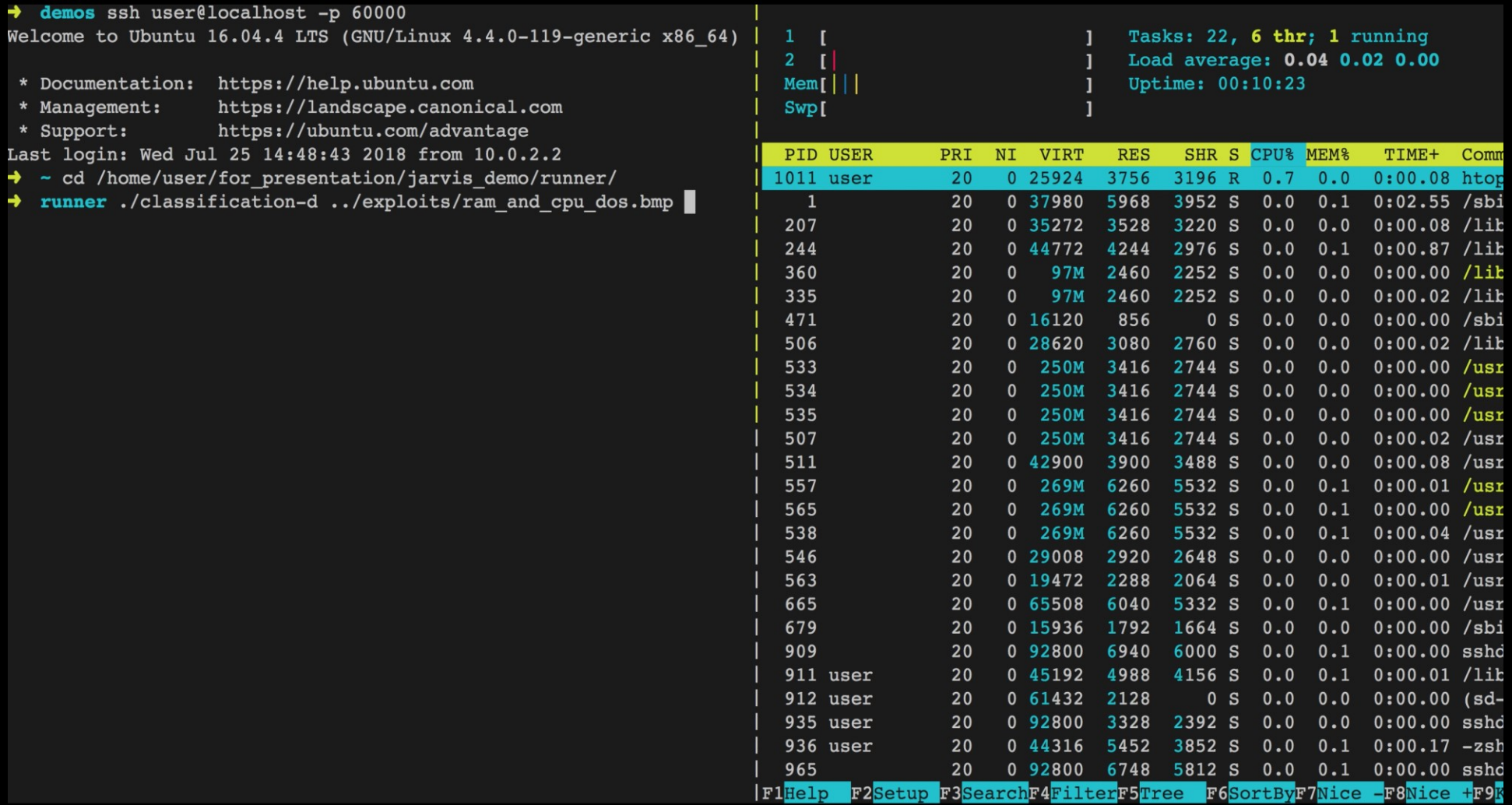

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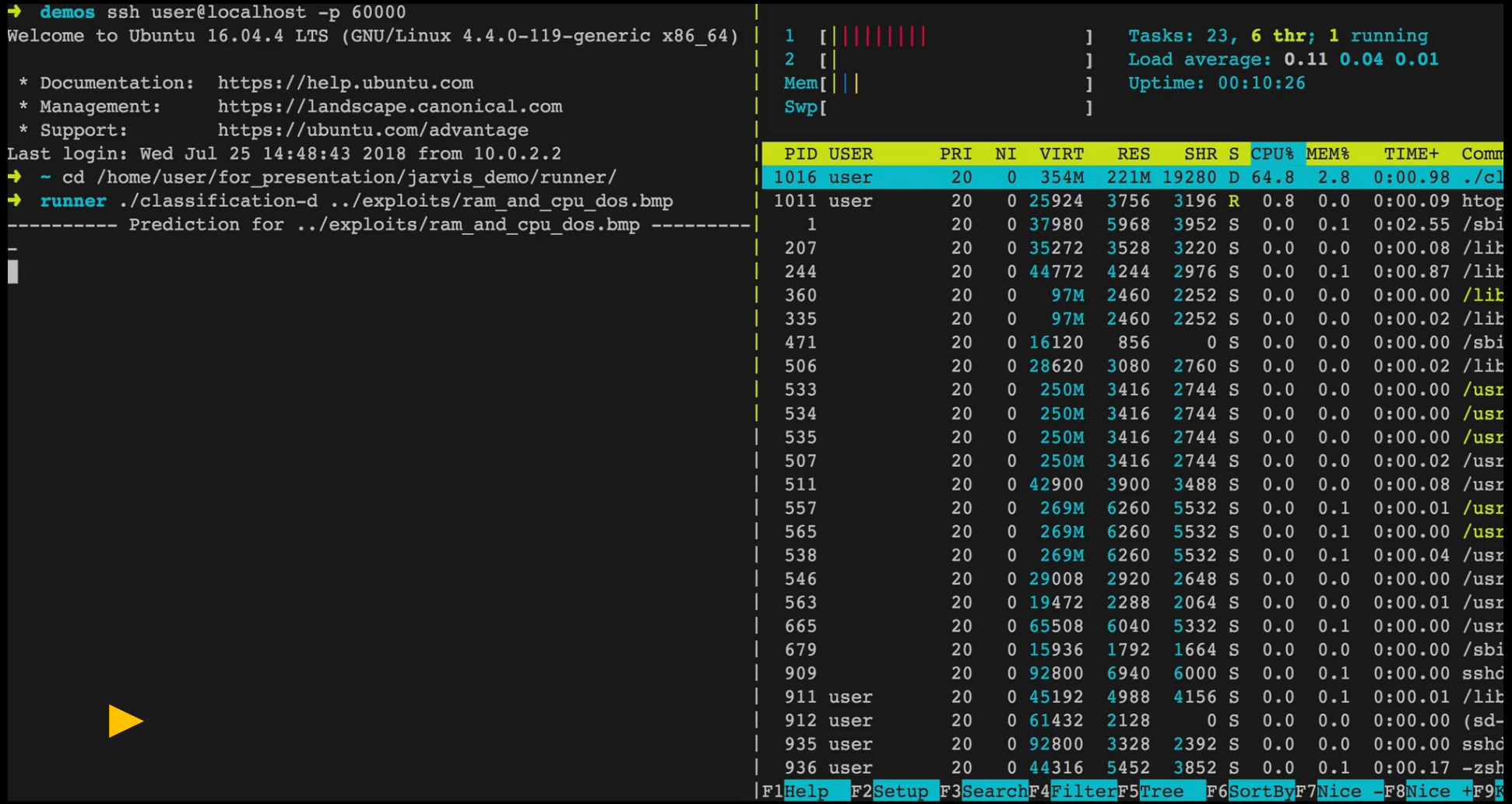

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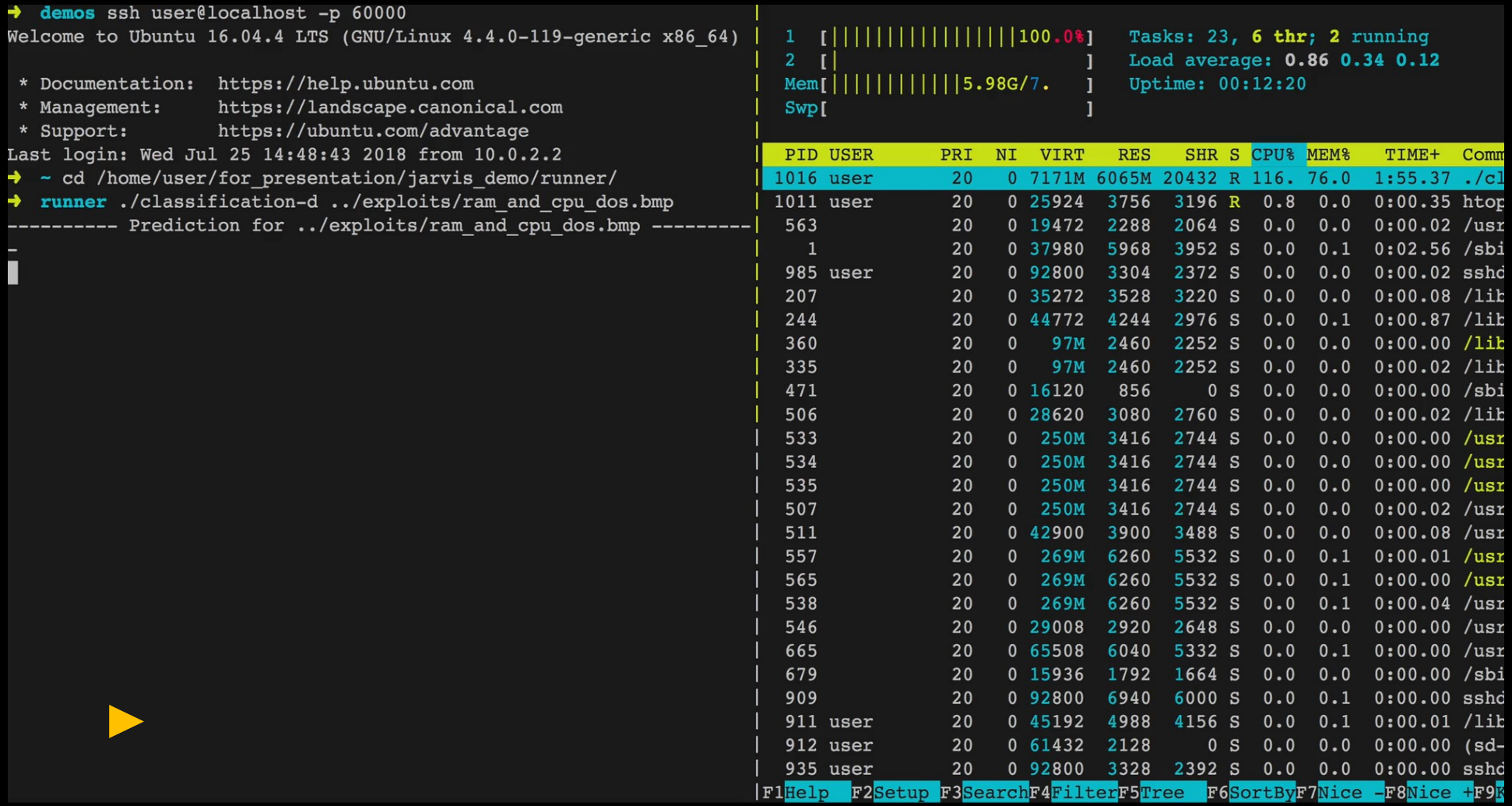
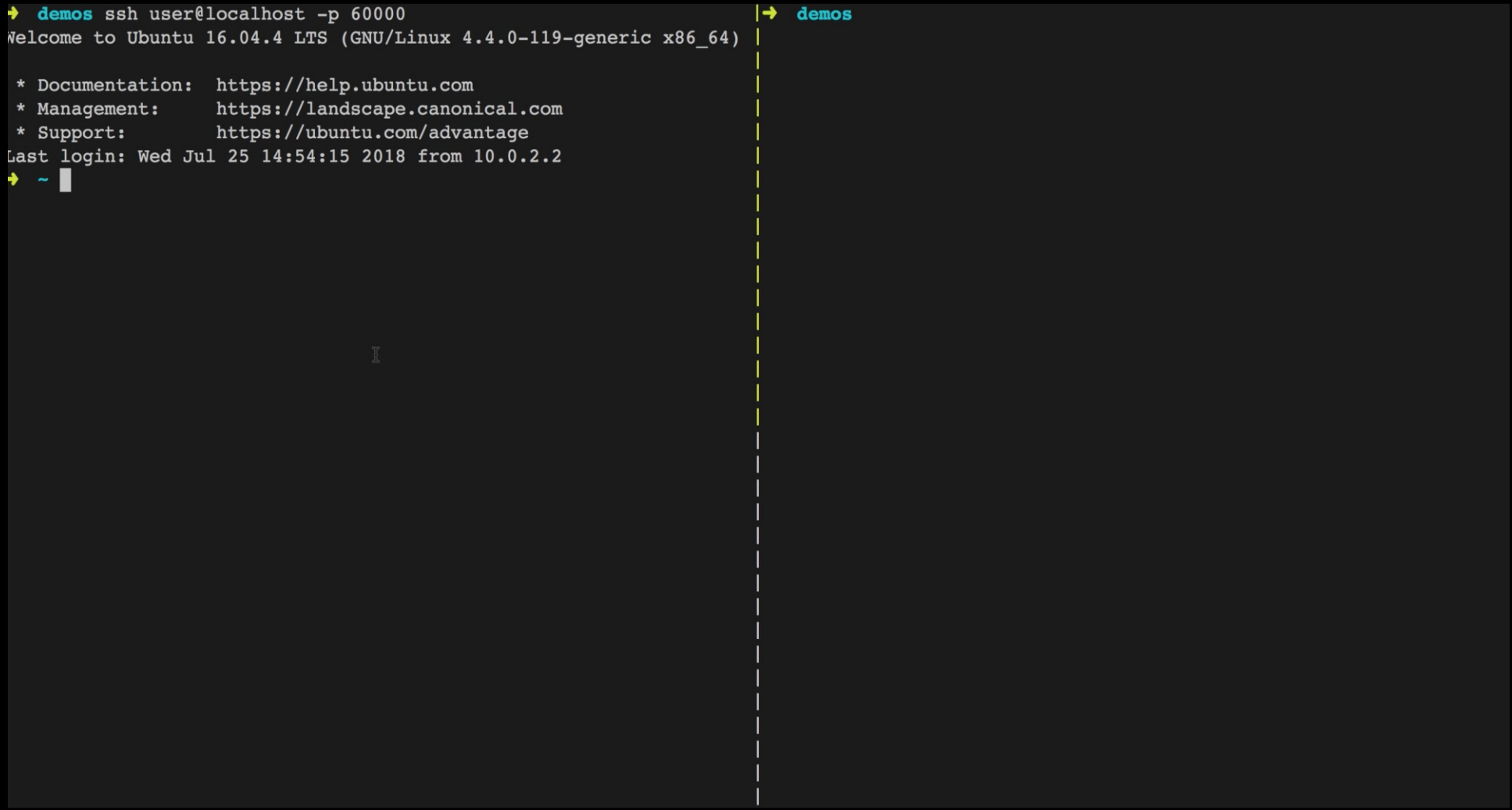
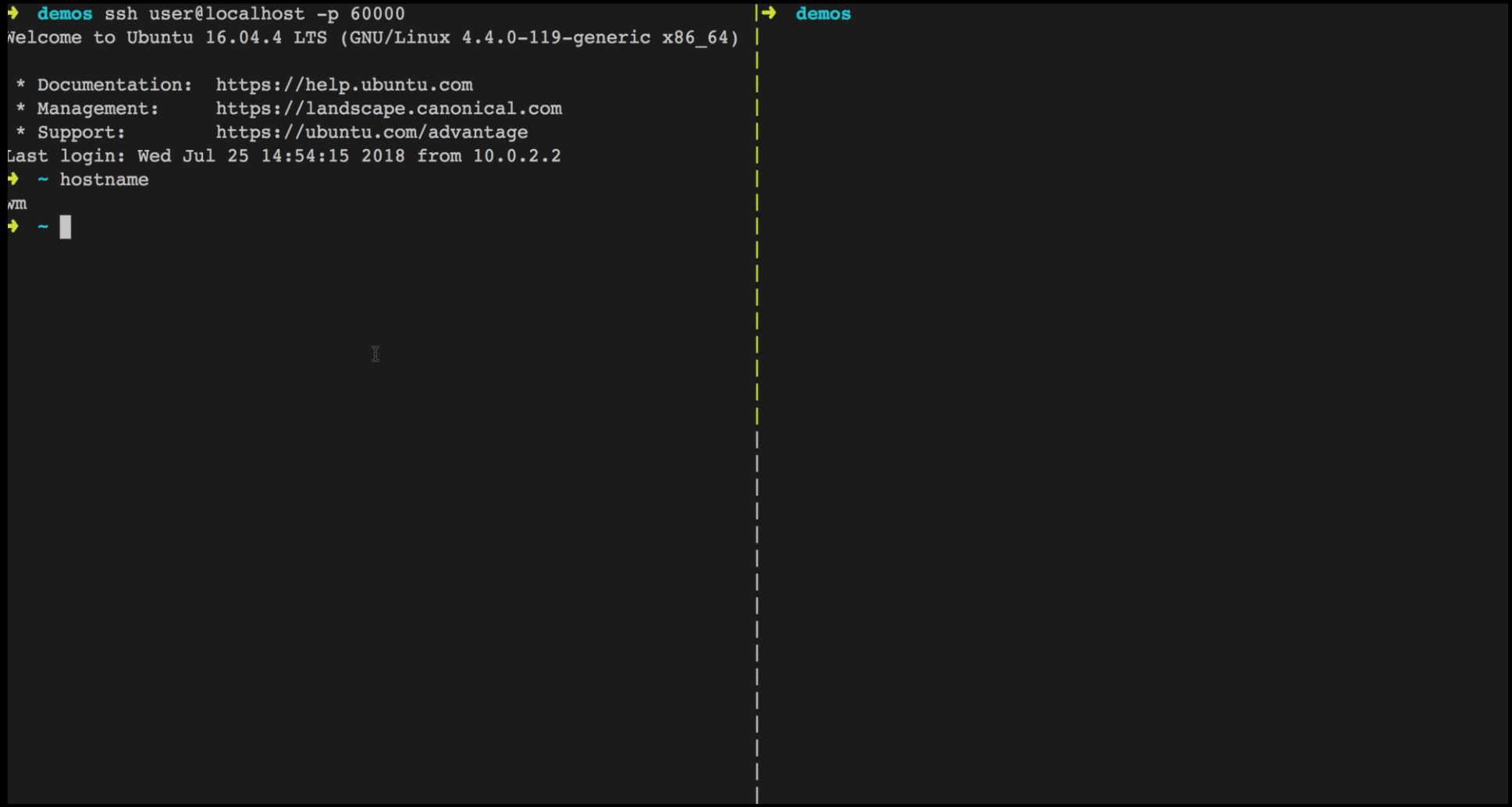


@barnhartguy @acaltum

DEMO TIME

Remote Code Execution (RCE)


demos ssh user@localhost -p 60000
Welcome to Ubuntu 16.04.4 LTS (GNU/Linux 4.4.0-119-generic x86_64)
* Documentation: https://help.ubuntu.com
* Management: https://landscape.canonical.com
* Support: https://ubuntu.com/advantage
Last login: Wed Jul 25 14:54:15 2018 from 10.0.2.2
~
demos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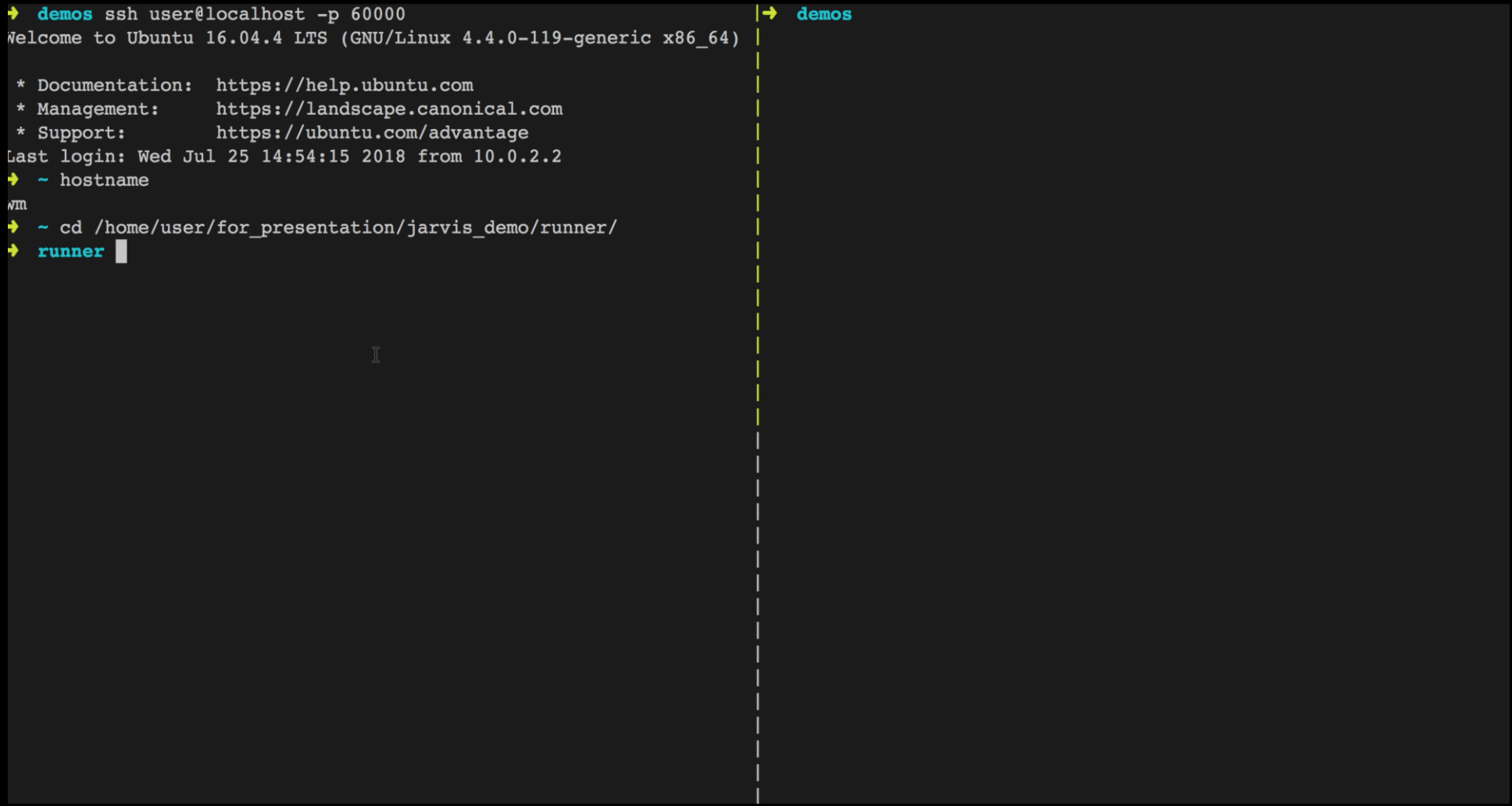
~ hostname
vm
~
demos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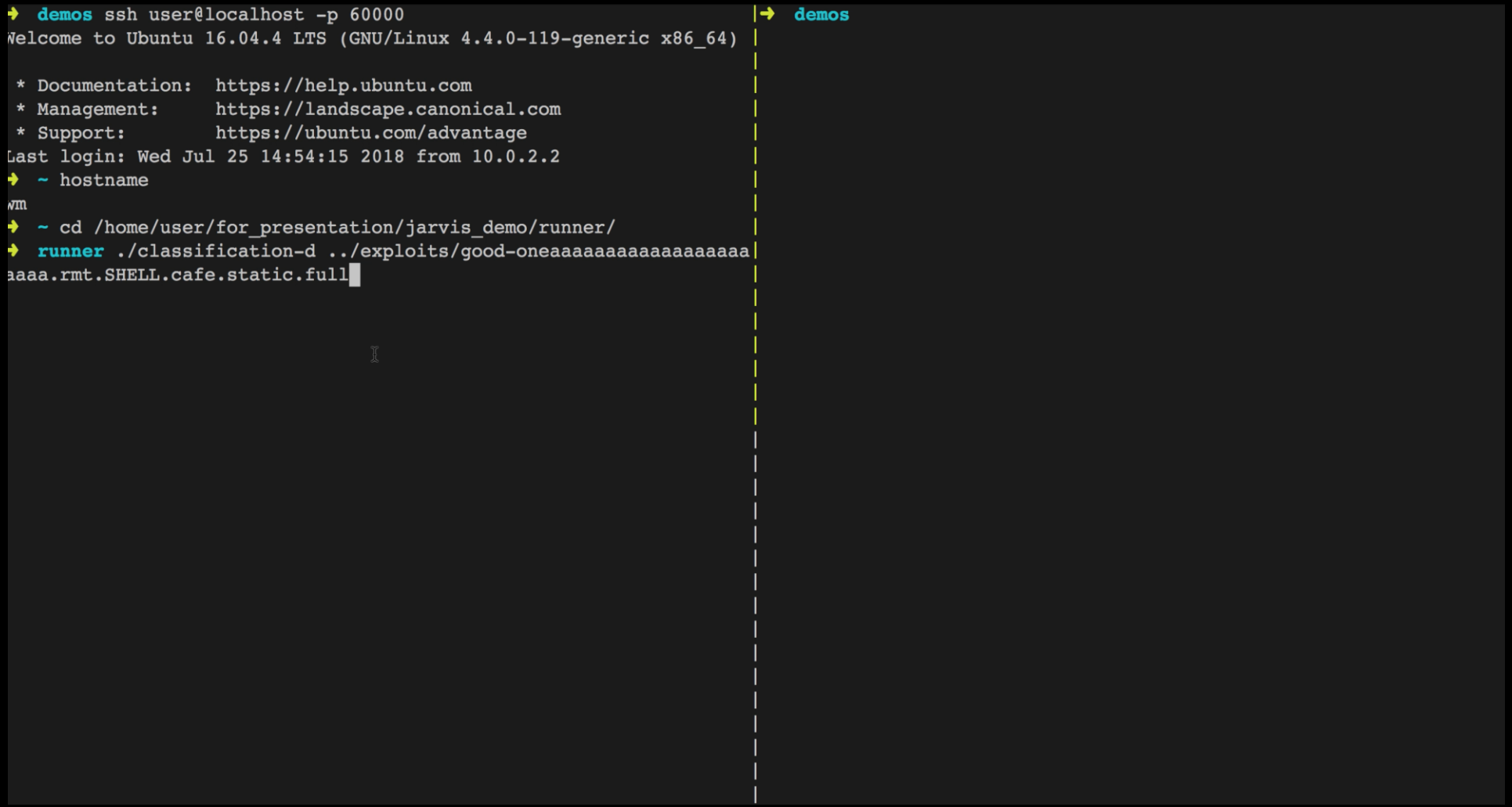
~ hostname
vm
~ cd /home/user/for_presentation/jarvis_demo/runner/
runner
demos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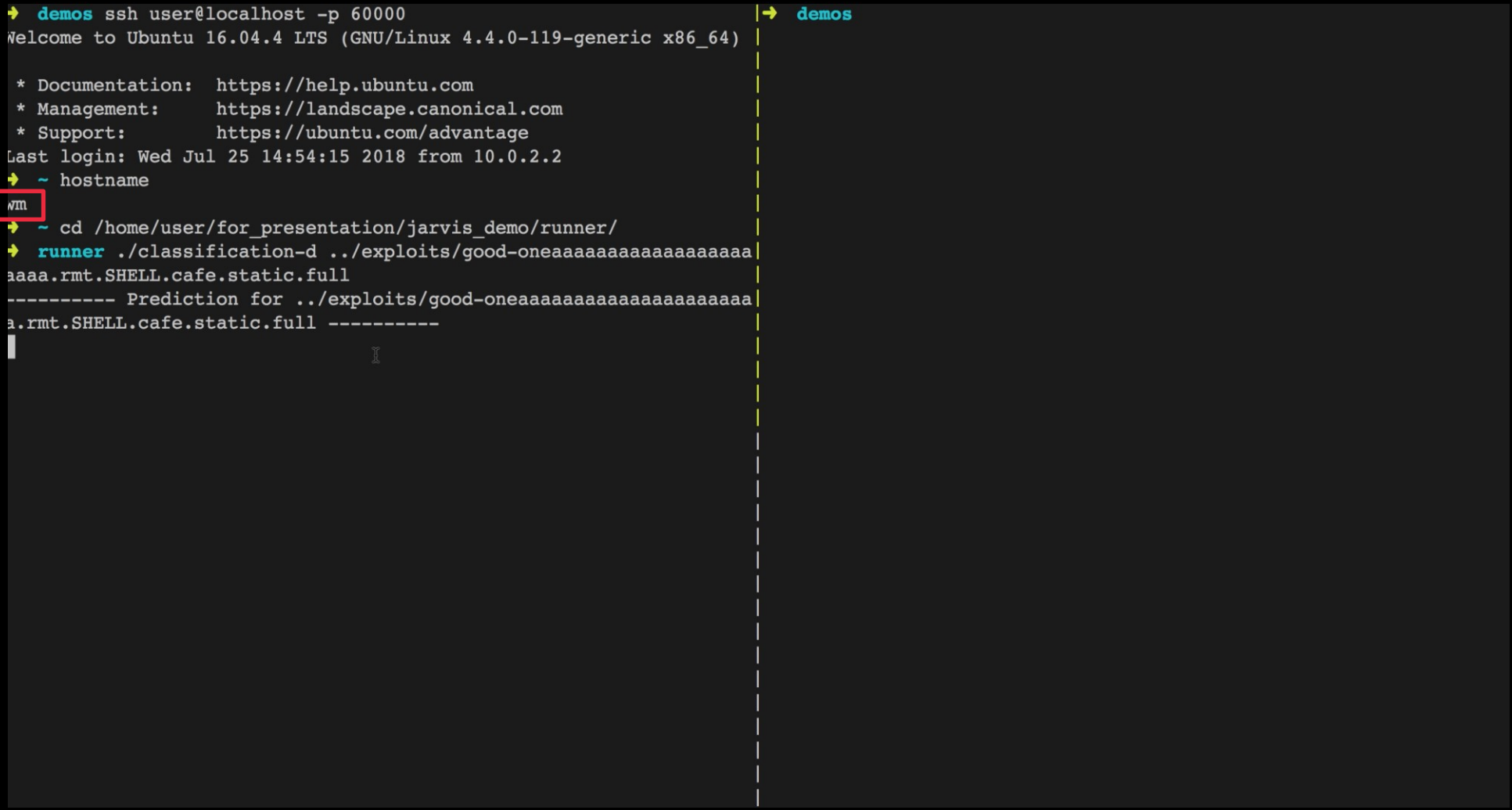
Last login: Wed Jul 25 14:54:15 2018 from 10.0.2.2
~ hostname
vm
~ cd /home/user/for_presentation/jarvis_demo/runner/
runner ./classification-d ../exploits/good-oneaaaaaaaaaaaaaaaaaaaa
aaaa.rmt.SHELL.cafe.static.full
demos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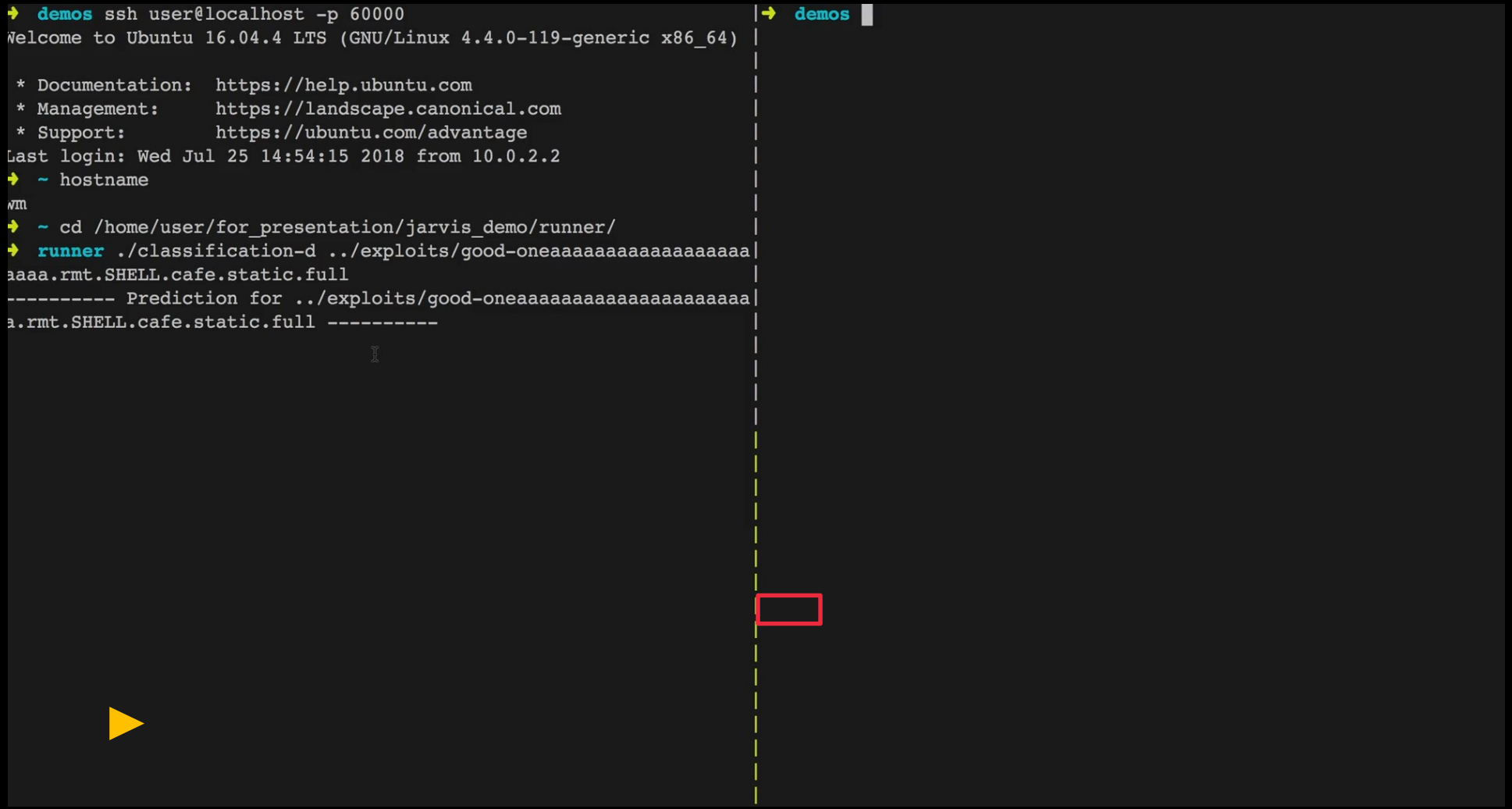
~ cd /home/user/for_presentation/jarvis_demo/runner/
runner ./classification-d ../exploits/good-oneaaaaaaaaaaaaaaaaaaa
aaaa.rmt.SHELL.cafe.static.full
---------- Prediction for ../exploits/good-oneaaaaaaaaaaaaaaaaaaaaa
a.rmt.SHELL.cafe.static.full ----------
demos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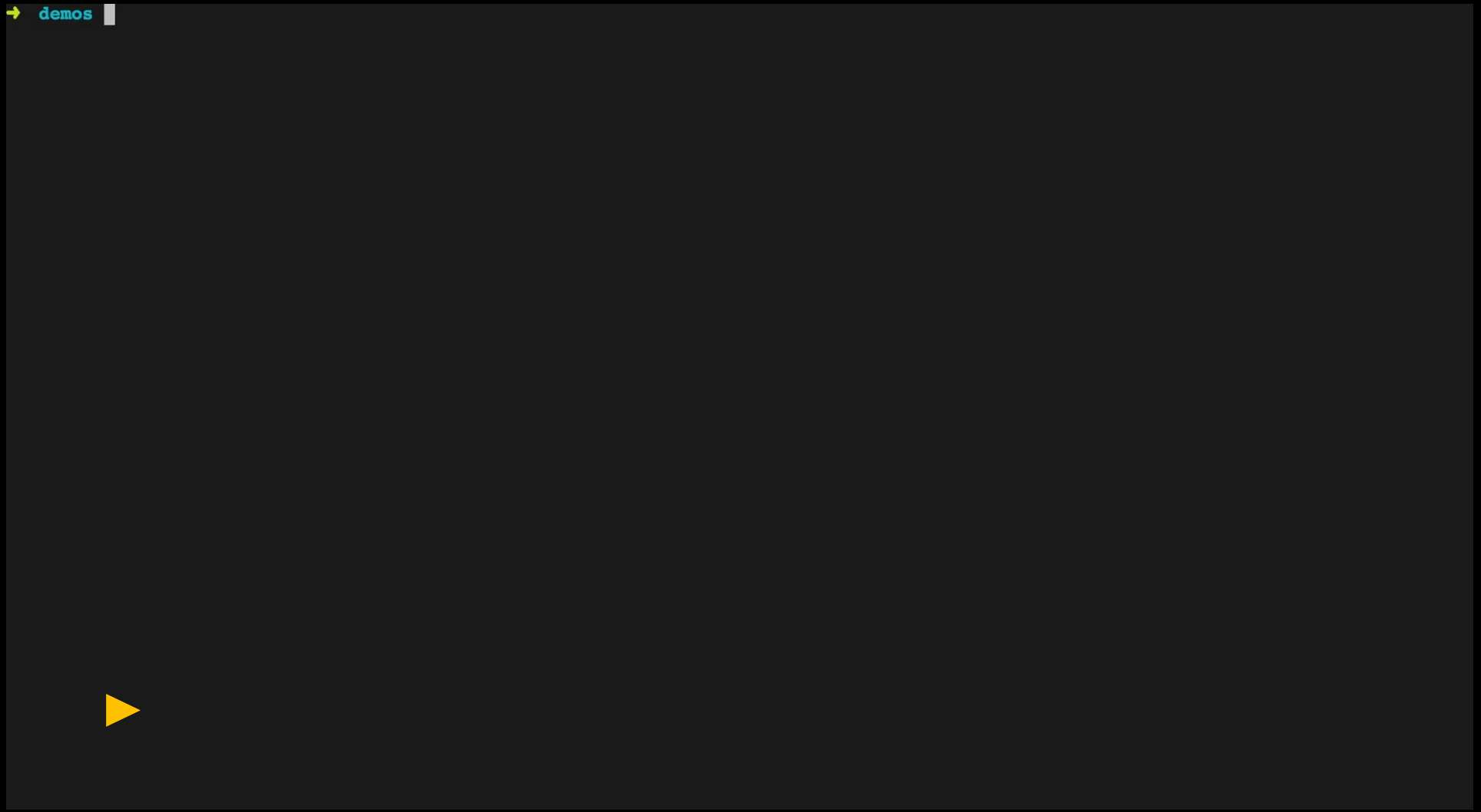
vm
~ cd /home/user/for_presentation/jarvis_demo/runner/
runner ./classification-d ../exploits/good-oneaaaaaaaaaaaaaaaaaaa
aaaa.rmt.SHELL.cafe.static.full
---------- Prediction for ../exploits/good-oneaaaaaaaaaaaaaaaaaaaa
a.rmt.SHELL.cafe.static.full ----------
demos

DEMO TIME

Model Tampering


demos

DEMO TIME

IP Theft

NO DEMO

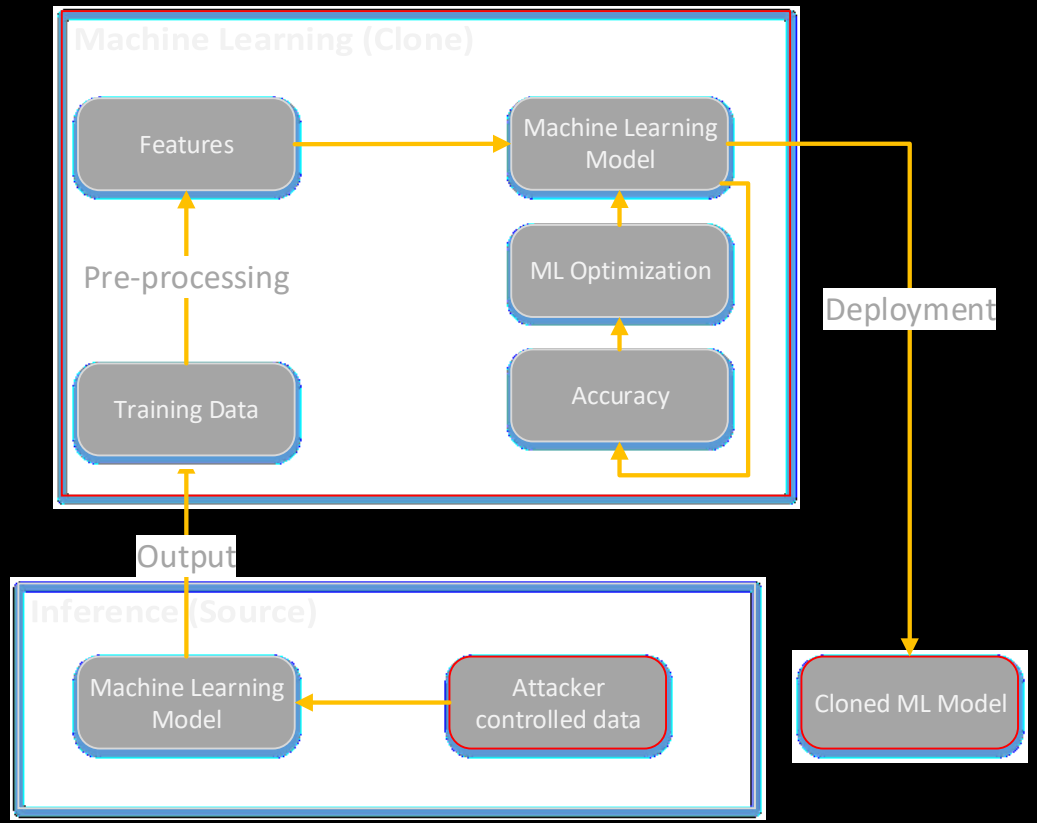
You actually saw this already ☺

SO MAYBE RCE IS KING AFTER ALL?

AND IF YOU DON'T HAVE AN RCE?

Let’s go after the algorithms!

ATTACK OF THE CLONES



CLONING

White box – full access to model and training data (Easy)

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Grey box – no access to model and training data, but educated guesses help (highly succesful)

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White box – full access to model and training data (Easy)

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Black box – no idea, exporation via probing, build a map (similar to a Reverse Engineering effort, research WIP)

WHAT IF THE ATTACKER HAS ACCESS TO THE TRAINING DATA?

BACKDOORS

Inject crafted data to the training set with label of your choice

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Inject crafted data to the training set with label of your choice

No known way to detect (or reverse engineer)!

This is still an open question academically

ENCODING

Learning is encoded in the matrix
You cannot reverse the matrix to learn “discover” made it learn specific things
Which means, there is no way to tell what it actually learned

This is also useful in other contexts…

DeepLocker

Concealing Targeted Attacks with AI Locksmithing

Dhilung Kirat, Jiyong Jang, Marc Ph. Stoecklin

IBM **Research**

MISS-PREDICTIONS (ADVERSARIAL ATTACKS)

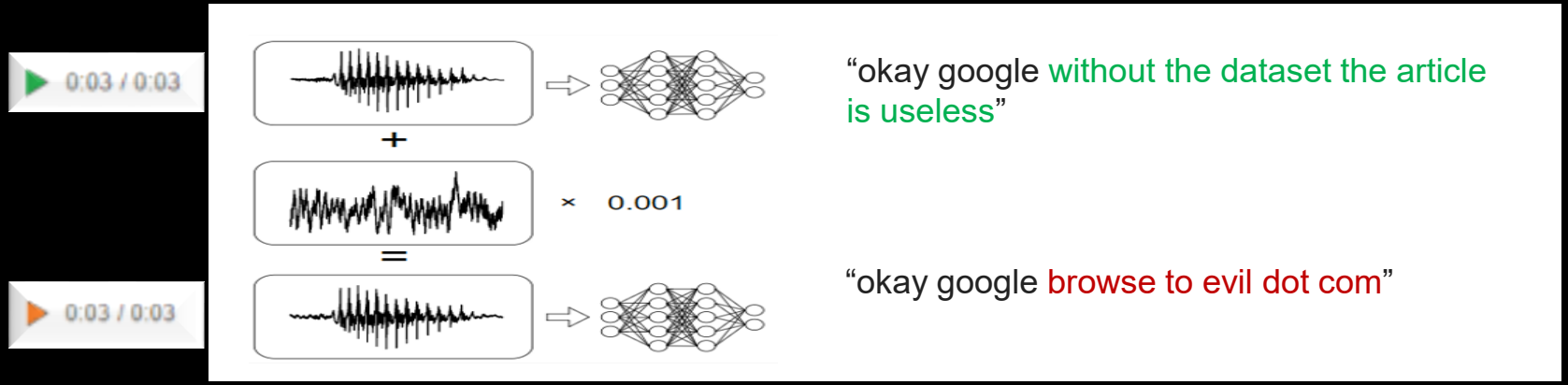
You can manipulate the output with a crafted input
;-)

Remember, the system optimizes for the “strongest signal”

TURTLE OR A RIFLE?

https://www.labsix.org/physical-objects-that-fool-neural-nets/

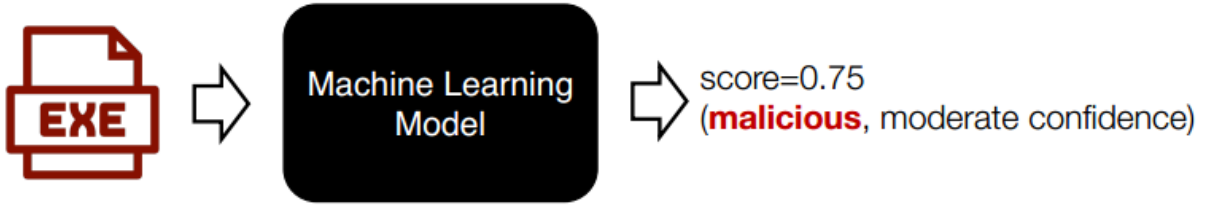
ADVERSARIAL AUDIO



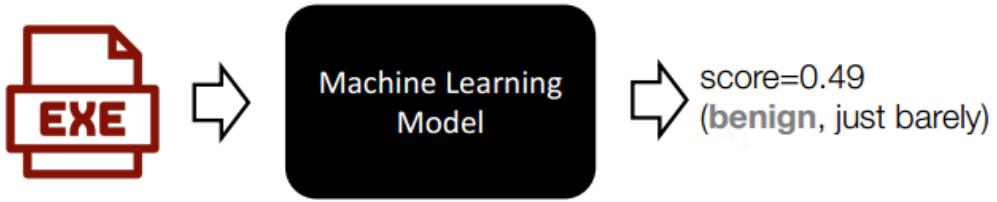
https://nicholas.carlini.com/code/audio_adversarial_examples/

EVADING NEXT GENERATION AV USING AI

- Static machine learning model trained on millions of samples



- Simple structural changes that don't change behavior
  - unpack
  - '.text' -> '.foo' (remains valid entry point)
  - create '.text' and populate with '.text from calc.exe'



https://media.defcon.org/DEF%20CON%2025/DEF%20CON%2025%20presentations/DEFCON-25-Hyrum-Anderson-Evading-Next-Gen-AV-Using-AI.pdf
https://www.youtube.com/watch?v=FGCle6T0Jpc

WHAT ABOUT PRIVACY ?

PRIVACY LEAKS? NOT YET, BUT SOON…

Risk: 7.4%

Risk: 35.3%

PRIVACY LEAKS? NOT YET, BUT SOON…

Risk: 96.2%

KEY TAKEAWAYS - RESEARCHERS

We need a better trust model for ML and a lot more research!

More focus should be on the infrastructure

The interfaces between the stages are very vulnerable (hint hint)

KEY TAKEAWAYS - ATTACKERS

This is a ripe field for attacks

High value targets

Huge dependency stack

KEY TAKEAWAYS - DEFENDERS

Machine Learning needs sanitation and security controls too

Use Machine Learning models from untrusted sources with caution

Validate the data you rely on - does it include negative cases? abnormal cases?


There is no AI.
It’s just someone else’s code.

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Evading next-gen AV using A.I.
For better machine-based malware analysis, add a slice of LIME
BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain

HOW TO PROCEED?

Come talk to us!

ANY QUESTIONS?

@barnhartguy @acaltum