FDL 2020

Robust Models for Source Code: Techniques and Applications

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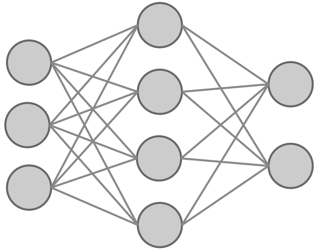
ETH zürich

SRILAB

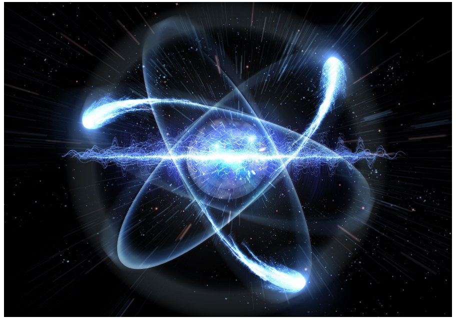
Secure, Reliable, and Intelligent Systems Lab @ ETH

Robust ML



Neural network verification

ML for programming



Probabilistic programming

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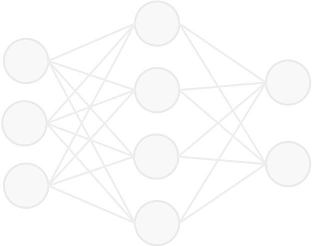
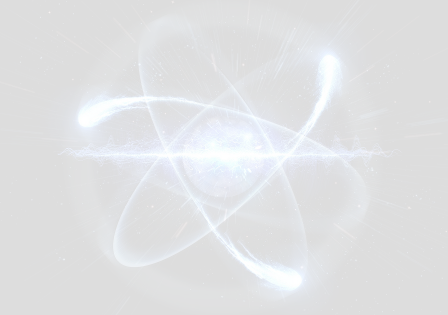
Robust ML



Neural network verification

ML for programming



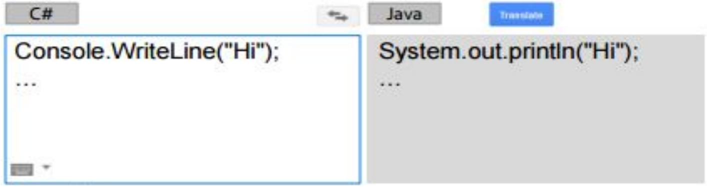
Probabilistic programming

Statistical Programming Tools

Code Completion

```
Camera camera = Camera.open();
camera.SetDisplayOrientation(90);
                  ?
```

Port Code

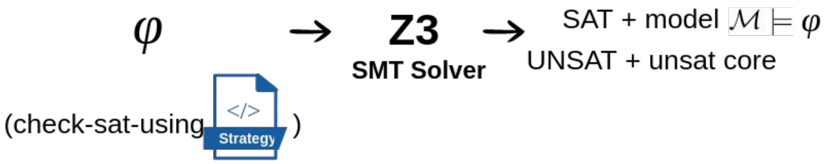


```
Console.WriteLine("Hi");
...
```

```
System.out.println("Hi");
...
```

Program Synthesis

Learning to Solve Formulas



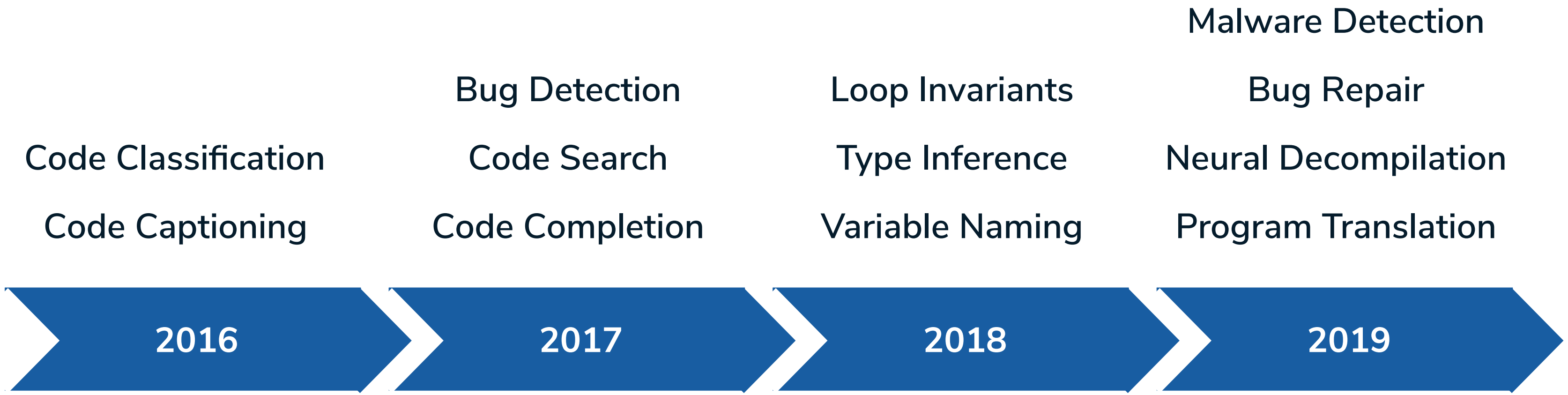
Up to 100x speed-up over Z3

Bug Detection

likely error

```
...
for x in range(a):
     print a[x]
```

Deep Learning + Code



2016

- Code Classification
- Code Captioning

2017

- Bug Detection
- Code Search
- Code Completion

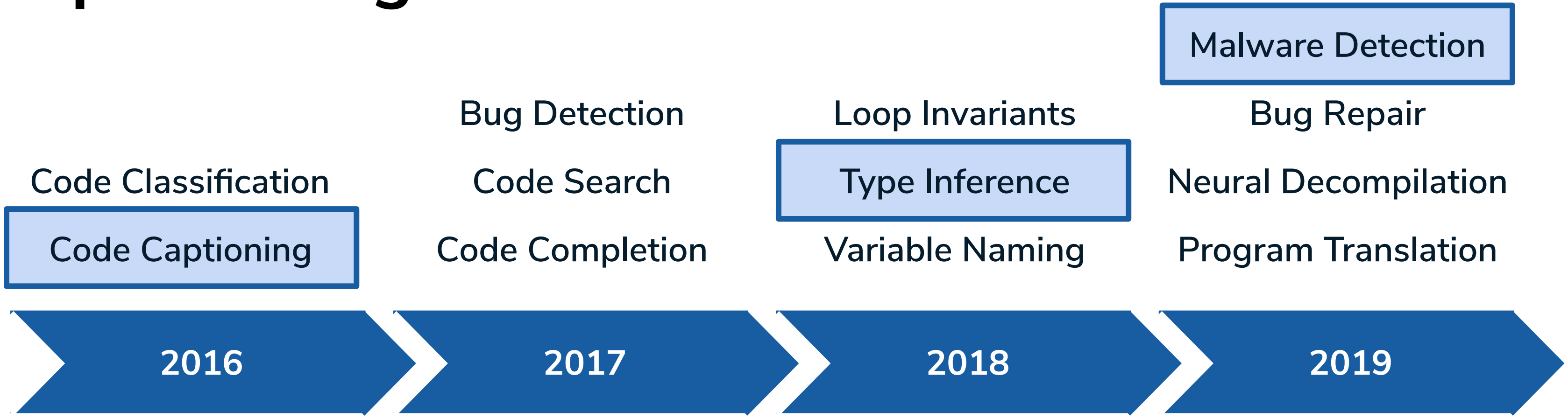
2018

- Loop Invariants
- Type Inference
- Variable Naming

2019

- Malware Detection
- Bug Repair
- Neural Decompilation
- Program Translation

Deep Learning + Code



Code Classification

Code Captioning

2016

Bug Detection

Code Search

Code Completion

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Loop Invariants

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2018

Malware Detection

Bug Repair

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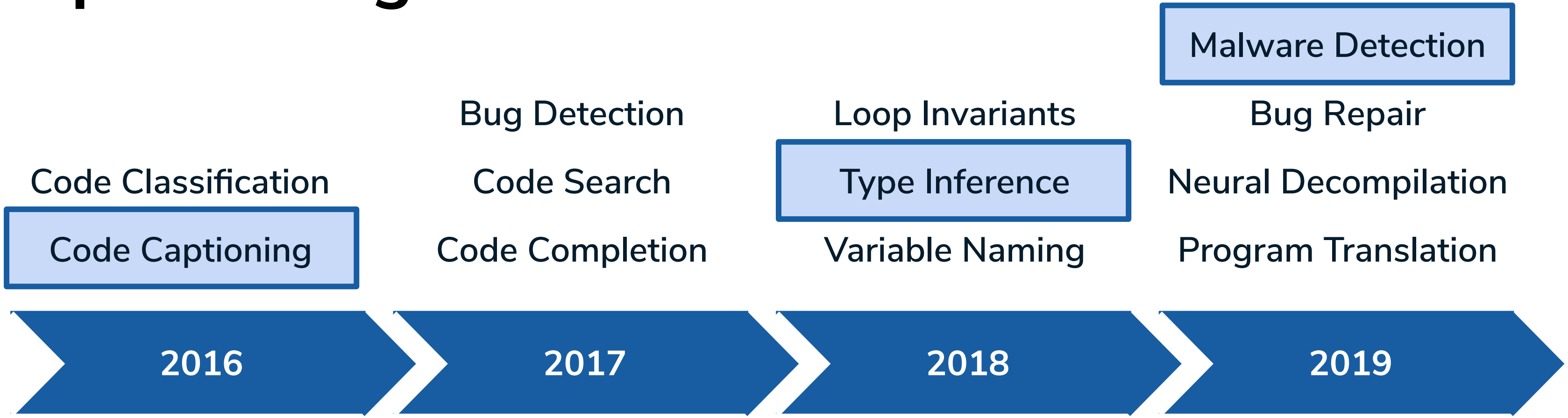
Program Translation

2019

Techniques are general and apply to other tasks

Deep Learning + Code



2016

Code Classification

Code Captioning

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Bug Detection

Code Search

Code Completion

2018

Loop Invariants

Type Inference

Variable Naming

2019

Malware Detection

Bug Repair

Neural Decompilation

Program Translation

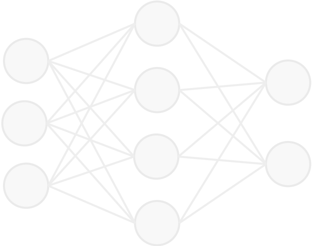
↑

Majority is based on deep learning models

Techniques are general and apply to other tasks

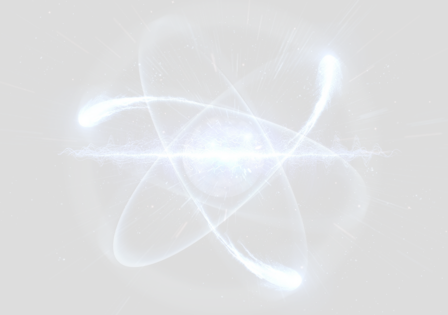
Secure, Reliable, and Intelligent Systems Lab @ ETH

Robust ML



Neural Network Verification

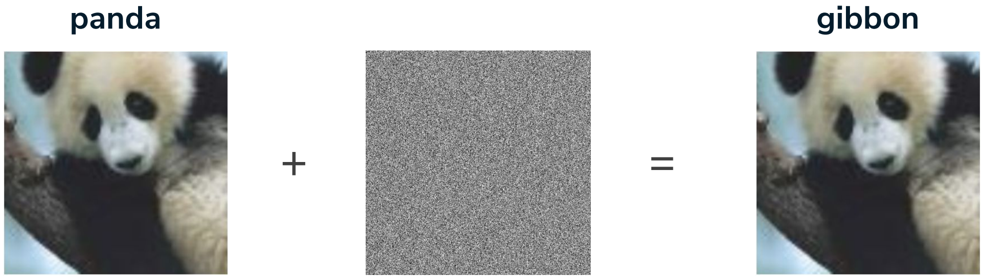
ML for programming



Probabilistic programming

Adversarial Robustness

Vision

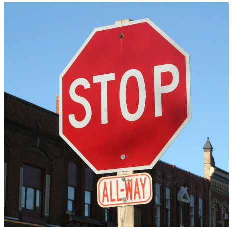


Explaining and Harnessing Adversarial Examples. Goodfellow et. al. ICLR’15

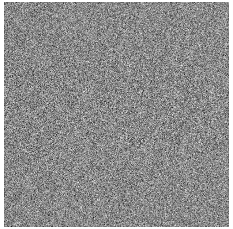
Adversarial Robustness

Vision

stop sign

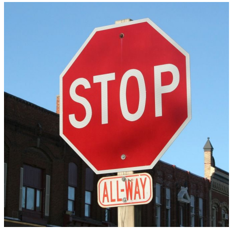


+



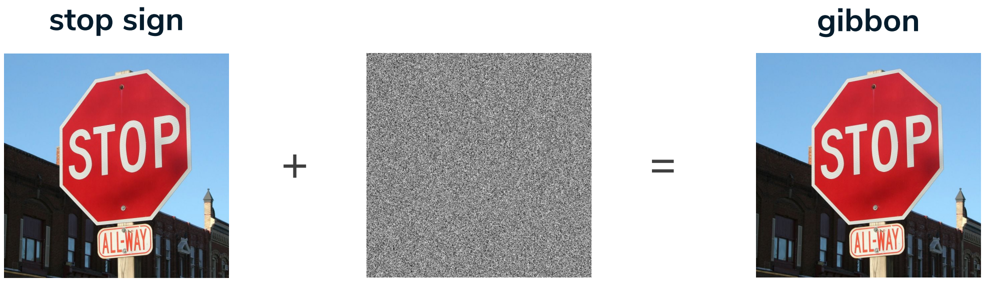
=

gibbon

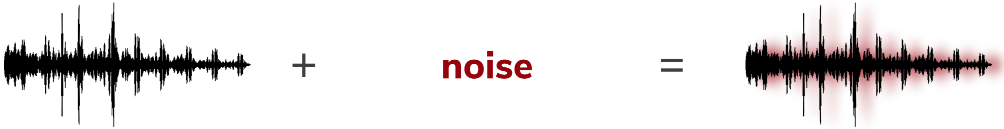


Adversarial Robustness

Vision



Sound



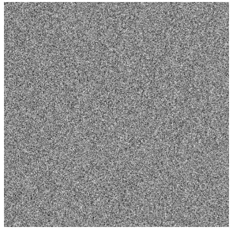
Audio Adversarial Examples: Targeted Attacks on Speech-to-Text. Carlini et. al. ICML'18 workshop

Adversarial Robustness

Vision

stop sign

+



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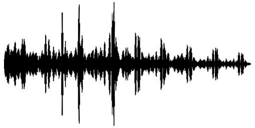
gibbon

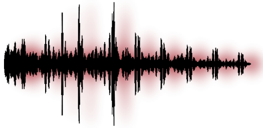
Sound



+

noise

=



Audio Adversarial Examples: Targeted Attacks on Speech-to-Text. Carlini et. al. ICML'18 workshop

Code

+

code refactoring

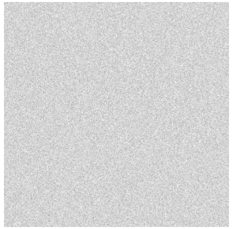
=

Adversarial Robustness

Vision

stop sign

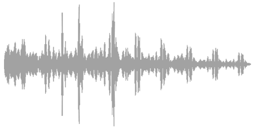
+



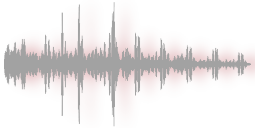
=

gibbon

Sound



+ noise =



Audio Adversarial Examples: Targeted Attacks on Speech-to-Text. Carlini et. al. ICML’18 workshop

Code

+ **code refactoring** =

Adversarial Robustness for Code

1 **How robust are existing models?**

</> Code

90% accuracy + **code refactoring** = **??** robustness

Adversarial Robustness for Code

1 **How robust are existing models?**

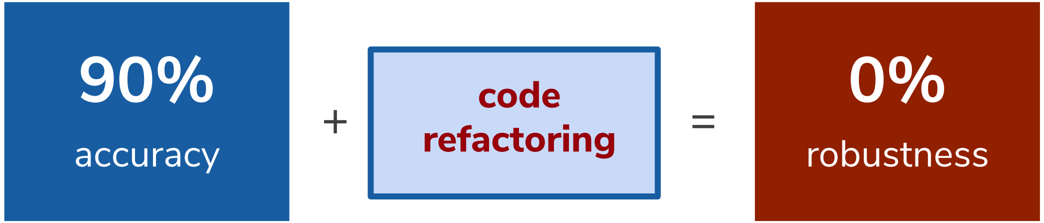
</> Code

90% accuracy + **code refactoring** = **0%** robustness

Adversarial Robustness for Code

1. How robust are existing models?
2. How to find adversarial examples?

</> Code



90% accuracy + code refactoring = 0% robustness

Adversarial Robustness for Code

1. How robust are existing models?
2. How to find adversarial examples?
3. How to improve robustness?

</> Code

90% accuracy + **code refactoring** = **0%** robustness ⇧

Adversarial Robustness Example

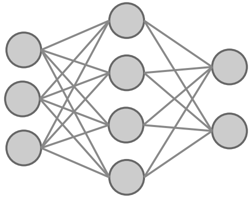
Input Program

x

```
...
v = parseInt(
  hex.substr(1),
  radix
)
...
```

Model

f(**x**) → **y**



(Type Inference)

Program Properties

y

```
...
v^num = parseInt^num(
  hex^str.substr^str(1),
  radix^num
)
...
```

Adversarial Robustness Example

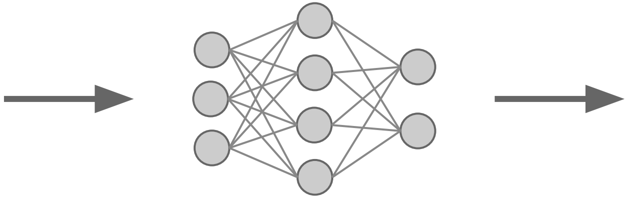
Input Program

x

```
...
v = parseInt(
  hex.substr(1),
  radix
)
...
```

Model

f(**x**) → **y**



(Type Inference)

Program Properties

y

$$\begin{array}{l}
\texttt{...} \\
\texttt{v}^{\texttt{num}}\texttt{ = parseInt}^{\texttt{num}}\texttt{(} \\
\quad\texttt{hex}^{\texttt{str}}\texttt{.substr}^{\texttt{str}}\texttt{(1),} \\
\quad\texttt{radix}^{\texttt{num}} \\
\texttt{)} \\
\texttt{...}
\end{array}$$

Goal (Adversarially Robustness):

Model is correct for *all* label preserving program transformations

```
...
v = parseInt(
  color.substr(1),
  radix
)
...
```

variable renaming

```
...
v = parseInt(
  hex.substr(42),
  radix
)
...
```

constant replacement

```
...
v = parseInt(
  hex.substr(1),
  radix + 0
)
...
```

semantic equivalence

```
...
parseInt(
  hex.substr(1),
  radix
)
...
```

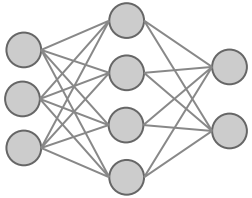
remove assignment

Adversarial Robustness Example

Input Program
x

```
...
v = parseInt(
  hex.substr(1),
  radix
)
...
```

Model
f(**x**) → **y**



(Type Inference)
Program Properties
y

```
...
v^num = parseInt^num(
  hex^str.substr^str(1),
  radix^num
)
...
```

Goal (Adversarially Robustness):
Model is correct for *all* label preserving program transformations

```
...
v = parseInt(
  color.substr(1),
  radix
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variable renaming

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v = parseInt(
  hex.substr(42),
  radix
)
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```

constant replacement

```
...
v = parseInt(
  hex.substr(1),
  radix + 0
)
...
```

semantic equivalence

```
...
parseInt(
  hex.substr(1),
  radix
)
...
```

remove assignment

S(x)

Set of valid program transformations for **x**

How robust are existing models?

Type Inference [1]

```
...
v^num = parseInt^num(
  hex^str.substr^str(1),
  radix^num
)
...
```

[1] Adversarial Robustness for Code. ICML’20

How robust are existing models?

Type Inference [1]

```
...
vnum = parseIntnum(
  hexstr.substrstr(1),
  radixnum
)
...
```

Code Captioning [2,3]

```
int indexOfTarget(Object target) {
  int i = 0;
  for (Object elem: this.elements) {
    if (elem.equals(target))
      return i
    i++;
  return -1;
}
```

[1] Adversarial Robustness for Code. ICML'20

[2] Adversarial Examples for Models of Code. ArXiv'19

[3] Semantic Robustness of Models of Source Code. ArXiv'20

How robust are existing models?

Type Inference [1]

```
...
vnum = parseIntnum(
  hexstr.substrstr(1),
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)
...
```

Code Captioning [2,3]

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int indexOfTarget(Object target) {
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  return -1;
}
```

Malware Detection [4]

```
push ebp
mov ebp, esp
push ebx
push edx                  yes
mov ebx, [ebp+4]          no
add ebx, 0x10
mov edx, [ebp+8]
mov [edx], ebx
```

[1] Adversarial Robustness for Code. ICML’20

[2] Adversarial Examples for Models of Code. ArXiv’19

[3] Semantic Robustness of Models of Source Code. ArXiv’20

[4] Optimization-Guided Binary Diversification to Mislead Neural Networks for Malware Detection. ArXiv’19

How robust are existing models?

Type Inference [1]

```
...
vnum = parseIntnum(
  hexstr.substrstr(1),
  radixnum
)
...
```

89% accuracy

48% robustness

Code Captioning [2,3]

```
int indexOfTarget(Object target) {
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39.2 F1

19.6 robust F1

Malware Detection [4]

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push edx                      yes
mov ebx, [ebp+4]              no
add ebx, 0x10
mov edx, [ebp+8]
mov [edx], ebx
```

99% accuracy

~2% robustness

[1] Adversarial Robustness for Code. ICML’20

[2] Adversarial Examples for Models of Code. ArXiv’19

[3] Semantic Robustness of Models of Source Code. ArXiv’20

[4] Optimization-Guided Binary Diversification to Mislead Neural Networks for Malware Detection. ArXiv’19

How robust are existing models?

Not trained with robustness in mind

Type Inference [1]

```
}
...
```

89% accuracy

48% robustness

Code Captioning [2,3]

```
int indexOfTarget(Object target) {
    i++;
  return -1;
}
```

39.2 F1

19.6 robust F1

Malware Detection [4]

```
push ebp
add ebx, 0x10
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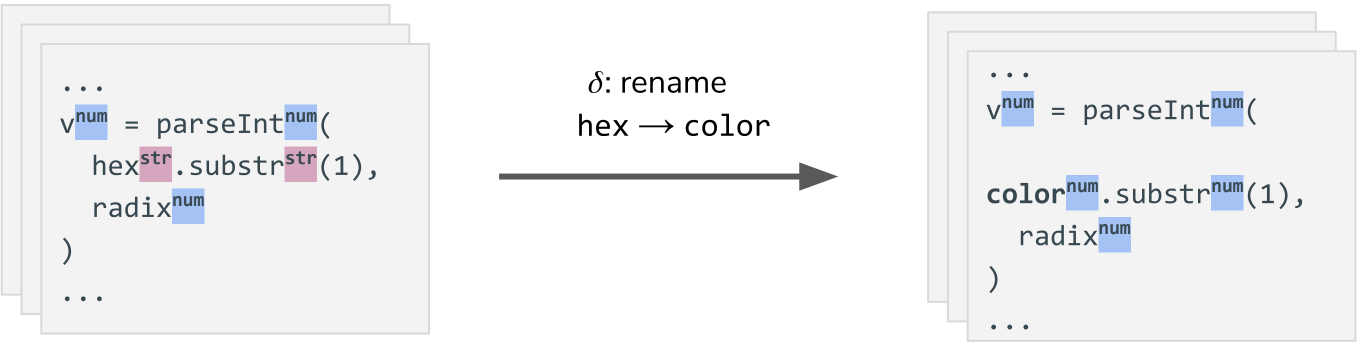
So Far...



original programs

```
...
v^num = parseInt^num(
  hex^str.substr^str(1),
  radix^num
)
...
```

δ: rename

hex ⟶ color

transformed programs

```
...
v^num = parseInt^num(

color^num.substr^num(1),
  radix^num
)
...
```

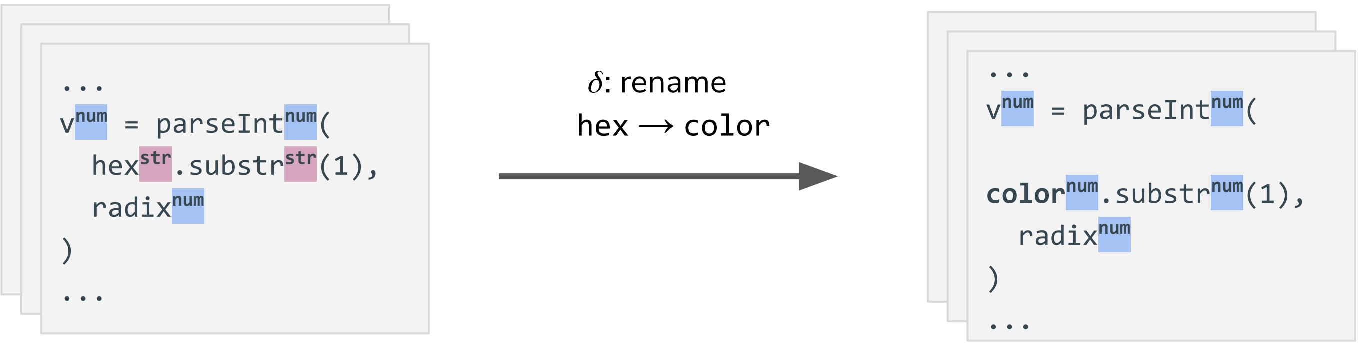
89%

accuracy

48%

robustness

Adversarial Training



original programs

```
...
v = parseInt(
  hex.substr(1),
  radix
)
...
```

δ: rename

`hex` → `color`

transformed programs

```
...
v = parseInt(

color.substr(1),
  radix
)
...
```

Standard training

$$\min \, loss(\theta, \mathbf{x}, \mathbf{y})$$

measures the model performance

Adversarial training

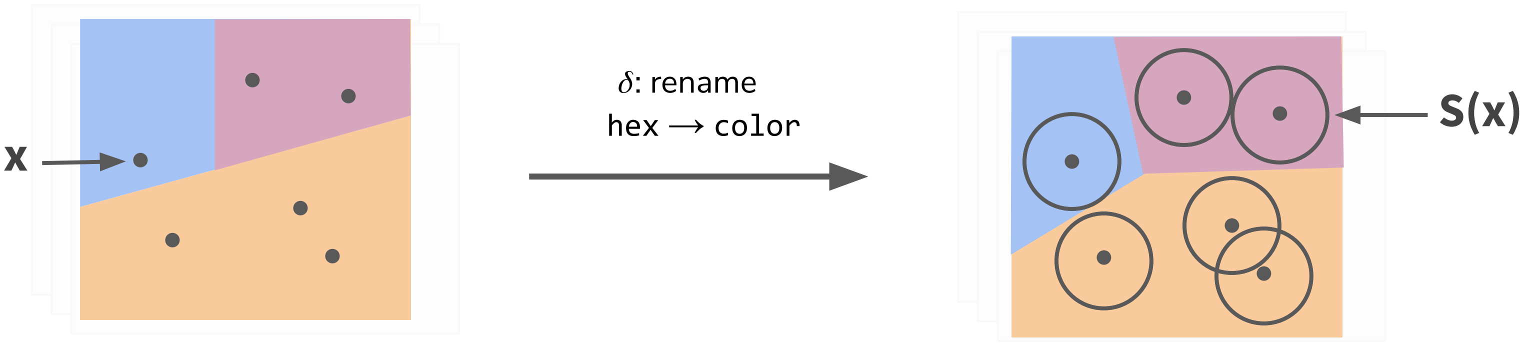
$$\min \left[\max_{\boldsymbol{\delta} \in \mathbf{S}(\mathbf{x})} loss(\theta, \mathbf{x} + \boldsymbol{\delta}, \mathbf{y}) \right]$$

program transformations

Adversarial Training

original programs

generated programs



Standard training

$$\min\ loss(\theta, \mathbf{x}, \mathbf{y})$$

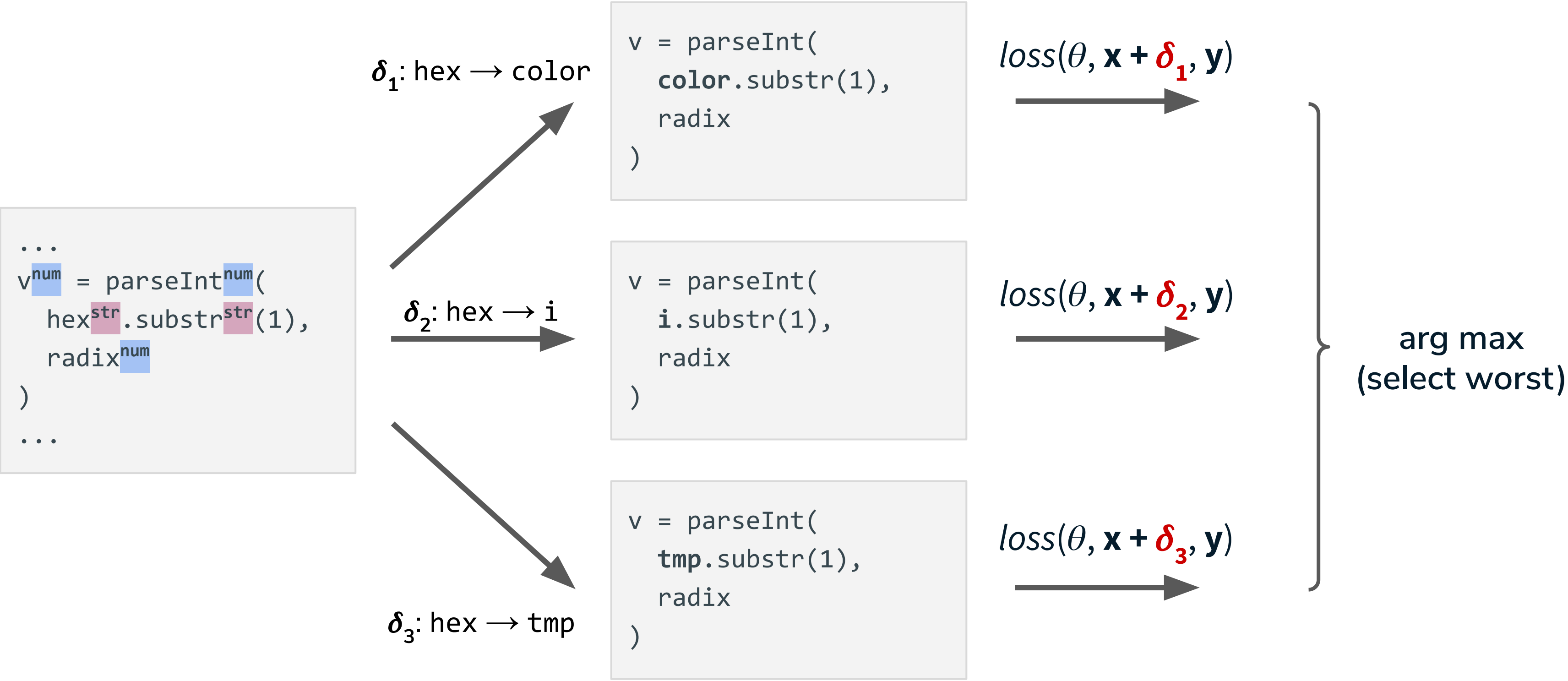
Adversarial training

$$\min\ [\max_{\boldsymbol{\delta} \in \mathbf{S}(\mathbf{x})} loss(\theta, \mathbf{x} + \boldsymbol{\delta}, \mathbf{y})]$$

trains on individual programs

trains on worst case generated programs

Finding Adversarial Examples



...

$\texttt{v}^{\texttt{num}}$ = $\texttt{parseInt}^{\texttt{num}}$(

  $\texttt{hex}^{\texttt{str}}$.$\texttt{substr}^{\texttt{str}}$(1),

  $\texttt{radix}^{\texttt{num}}$

)

...

$\boldsymbol{\delta}_1$: hex → color

```
v = parseInt(
  color.substr(1),
  radix
)
```

$loss(\theta, \mathbf{x} + \boldsymbol{\delta}_1, \mathbf{y})$

$\boldsymbol{\delta}_2$: hex → i

```
v = parseInt(
  i.substr(1),
  radix
)
```

$loss(\theta, \mathbf{x} + \boldsymbol{\delta}_2, \mathbf{y})$

$\boldsymbol{\delta}_3$: hex → tmp

```
v = parseInt(
  tmp.substr(1),
  radix
)
```

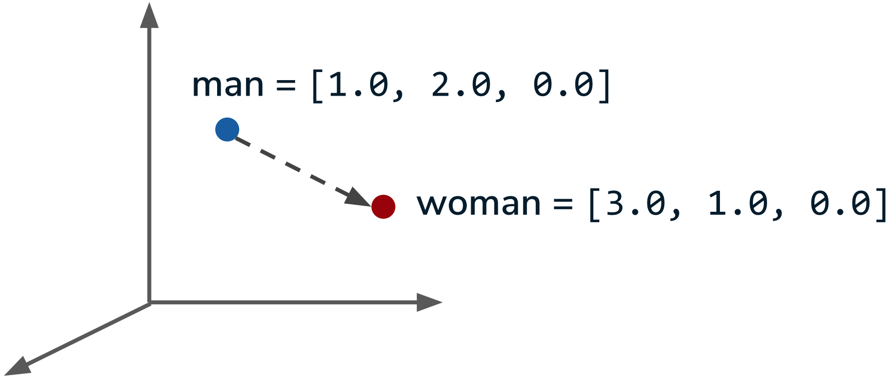
$loss(\theta, \mathbf{x} + \boldsymbol{\delta}_3, \mathbf{y})$

arg max
(select worst)

Basic approach: Try all valid modifications

Word Embeddings

maps each **discrete word** to a **continuous vector**



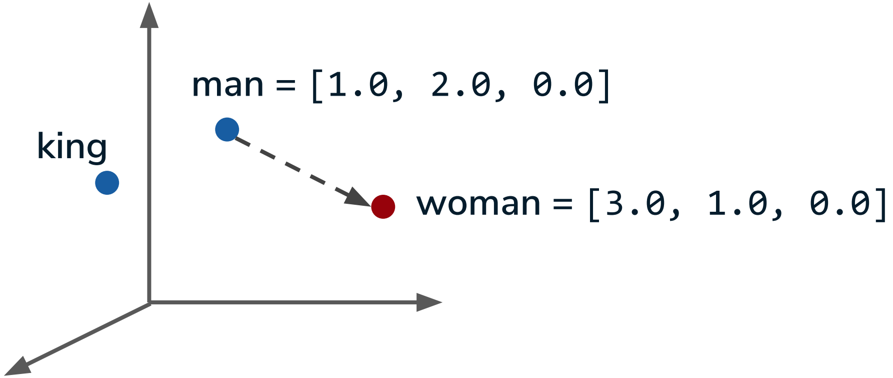
man = [1.0, 2.0, 0.0]

woman = [3.0, 1.0, 0.0]

Distributed Representations of Words and Phrases and their Compositionality. Mikolov et. al. NeurIPS’13

Word Embeddings

maps each **discrete word** to a **continuous vector**



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Word Embeddings

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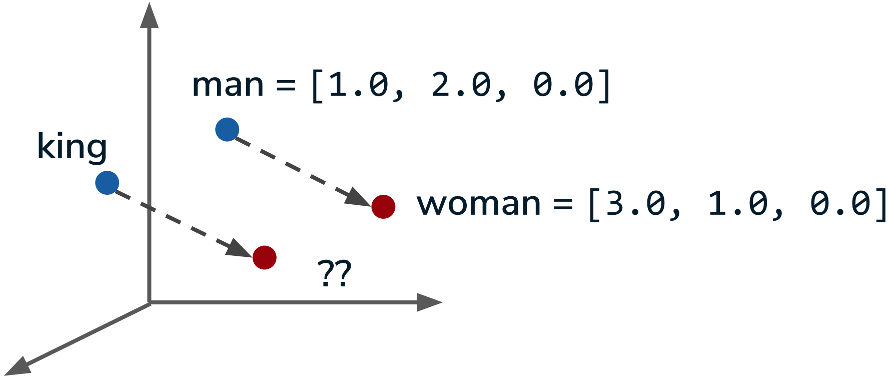

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Word Embeddings

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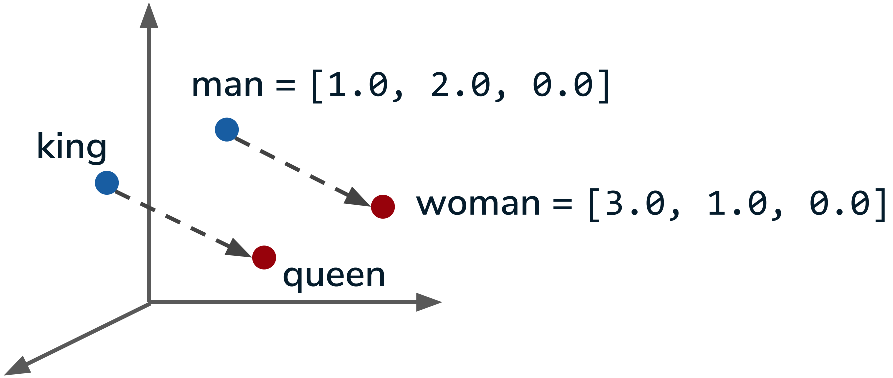

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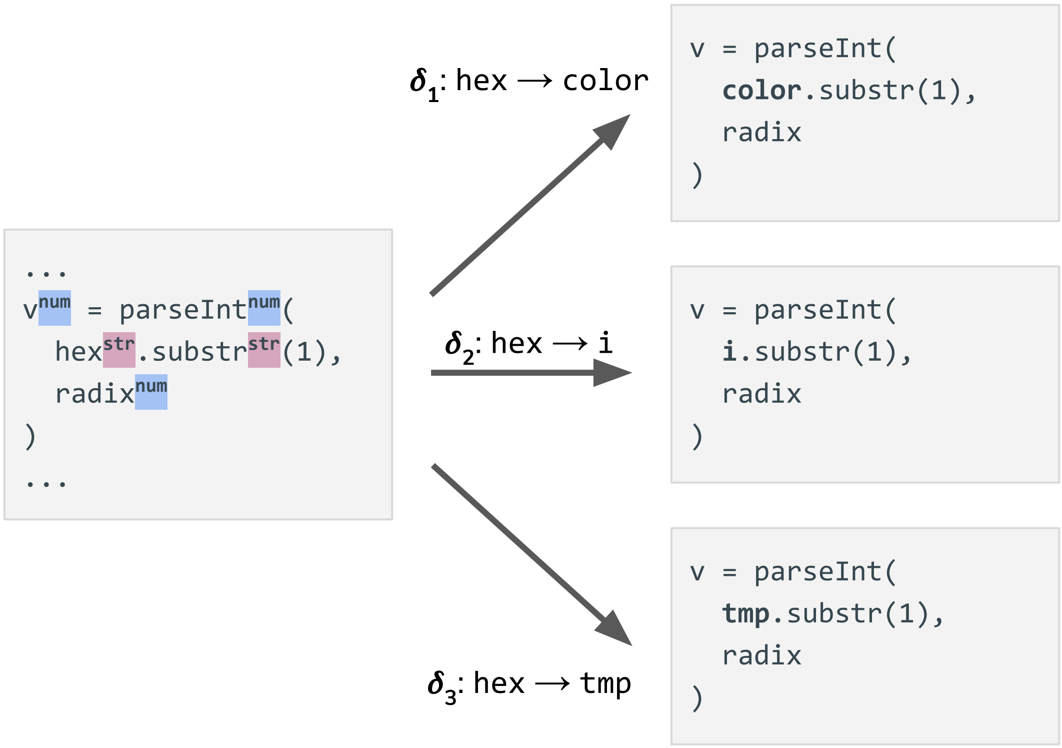
Finding Adversarial Examples



...
v^{num} = parseInt^{num}(
  hex^{str}.substr^{str}(1),
  radix^{num}
)
...

$\boldsymbol{\delta}_1$: hex ⟶ color

```
v = parseInt(
  color.substr(1),
  radix
)
```

$\boldsymbol{\delta}_2$: hex ⟶ i

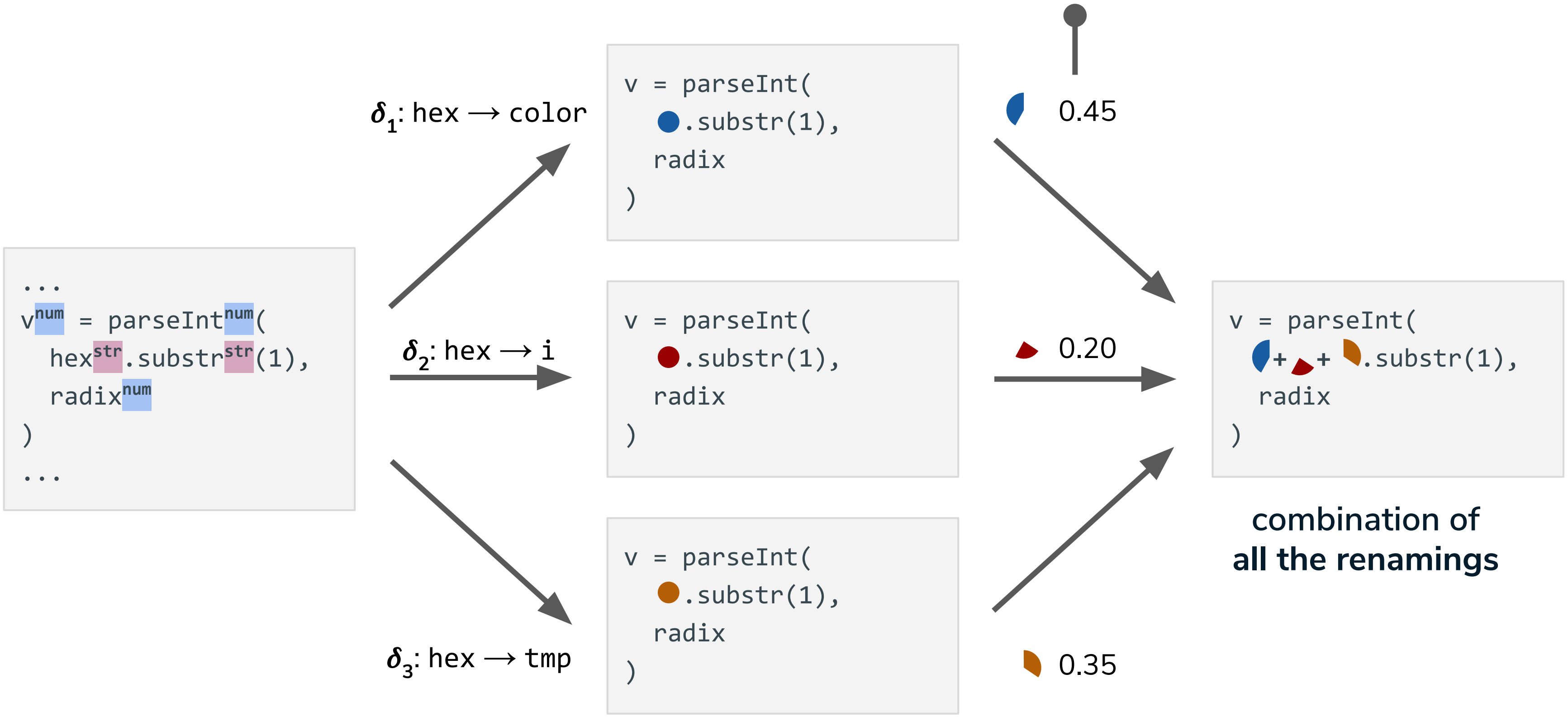
```
v = parseInt(
  i.substr(1),
  radix
)
```

$\boldsymbol{\delta}_3$: hex ⟶ tmp

```
v = parseInt(
  tmp.substr(1),
  radix
)
```

Finding Adversarial Examples

renaming weight



```
...
v = parseInt(
  hex.substr(1),
  radix
)
...
```

δ_1: hex → color

```
v = parseInt(
  ●.substr(1),
  radix
)
```

0.45

δ_2: hex → i

```
v = parseInt(
  ●.substr(1),
  radix
)
```

0.20

δ_3: hex → tmp

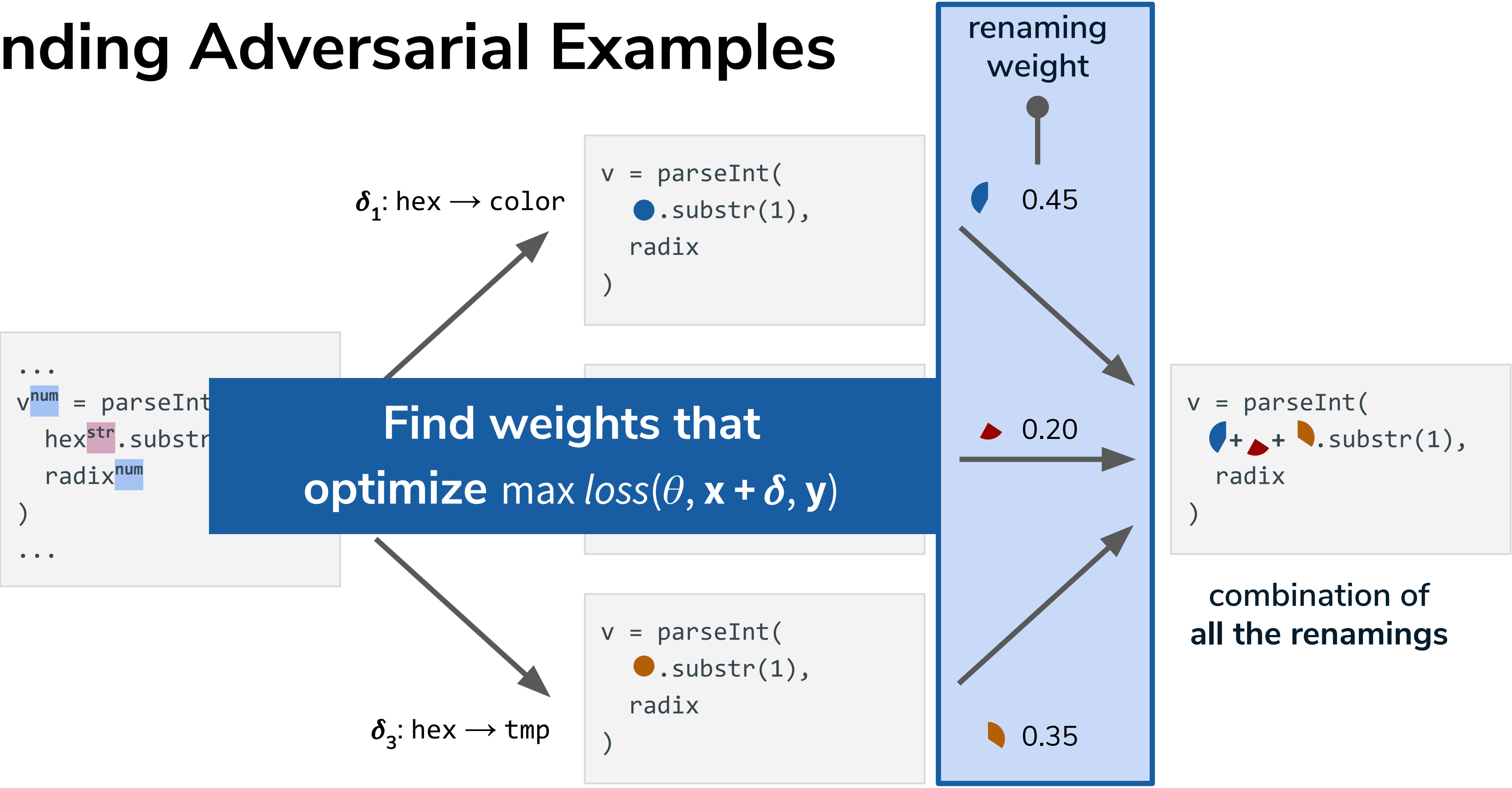
```
v = parseInt(
  ●.substr(1),
  radix
)
```

0.35

```
v = parseInt(
  ◖+◣+◗.substr(1),
  radix
)
```

combination of
all the renamings

Finding Adversarial Examples



```
...
v = parseInt
  hex.substr
  radix
)
...
```

δ_1: hex → color

```
v = parseInt(
  ●.substr(1),
  radix
)
```

δ_3: hex → tmp

```
v = parseInt(
  ●.substr(1),
  radix
)
```

Find weights that optimize $\max loss(\theta, \mathbf{x} + \delta, \mathbf{y})$

```
v = parseInt(
  ● + ● + ●.substr(1),
  radix
)
```

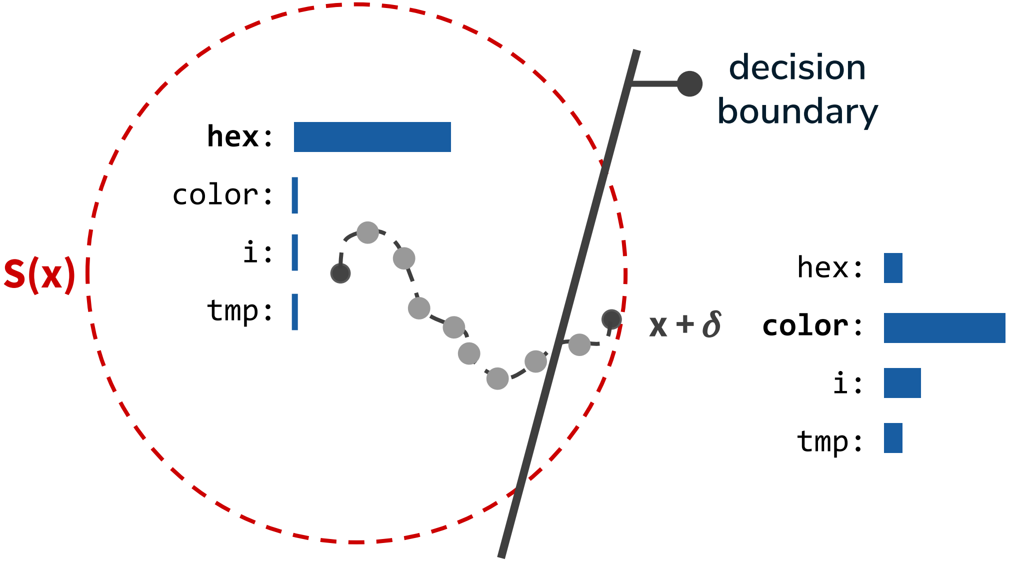
combination of
all the renamings

Solving the Inner max *loss* Efficiently

Gradient Based Optimization

$$\theta \leftarrow \theta - \nabla_{\boldsymbol{\delta}}\, loss(\theta, \mathbf{x} + \boldsymbol{\delta}, \mathbf{y})$$

$\boldsymbol{\delta} \in \mathbf{S(x)}$



Adversarial Examples for Models of Code.
Yefet et. al. ArXiv'20

Robustness of Existing Models

Type Inference [1]

```
...
v^num = parseInt^num(
  hex^str.substr^str(1),
  radix^num
)
...
```

89% accuracy

45% robustness

Adversarial training

57% robustness

Code Captioning [2,3]

```
int indexOfTarget(Object target) {
  int i = 0;
  for (Object elem: this.elements) {
    if (elem.equals(target))
      return i
    i++;
  return -1;
}
```

39.2 F1

19.6 robust F1

Malware Detection [4]

```
push ebp
mov ebp, esp
push ebx
push edx                yes
mov ebx, [ebp+4]        no
add ebx, 0x10
mov edx, [ebp+8]
mov [edx], ebx
```

99% accuracy

~2% robustness

Robustness of Existing Models

Type Inference [1]

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...
vnum = parseIntnum(
  hexstr.substrstr(1),
  radixnum
)
...
```

89%	45%
accuracy	robustness

Adversarial training

57%
robustness

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39.2	19.6
F1	robust F1
40.6	27.5
F1	robust F1

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too expensive

Solving the Inner max *loss* Efficiently

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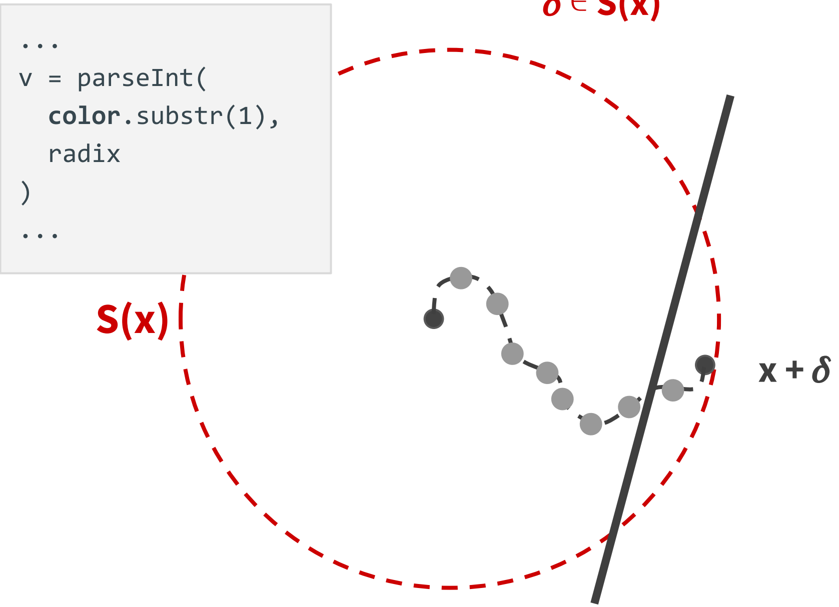
$$\boldsymbol{\delta} \in \mathbf{S}(\mathbf{x})$$

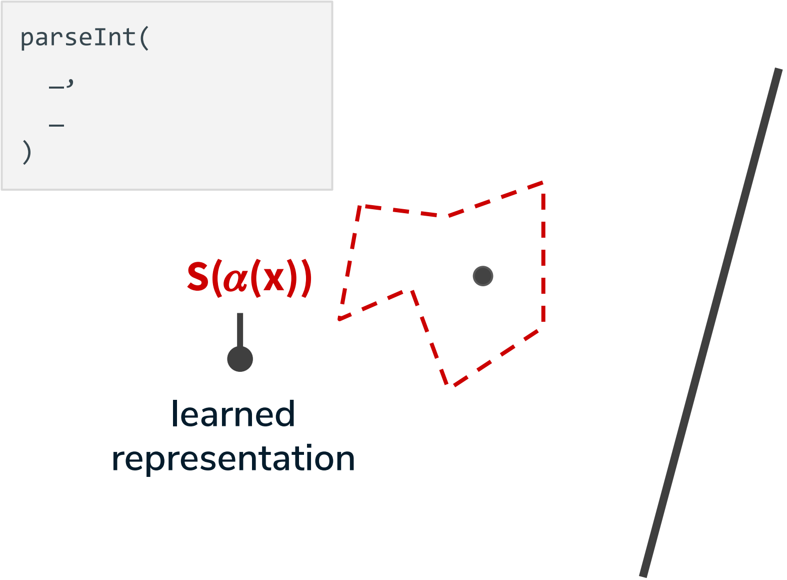


```
...
v = parseInt(
  color.substr(1),
  radix
)
...
```

Refine S

$$\min\,[\max\, loss(\theta, \mathbf{x} + \boldsymbol{\delta}, \mathbf{y})]$$

$$\boldsymbol{\delta} \in \mathbf{S}(\alpha(\mathbf{x}))$$



```
parseInt(
  _,
  _
)
```

Adversarial Robustness for Code.
Bielik et. al. ICML’20

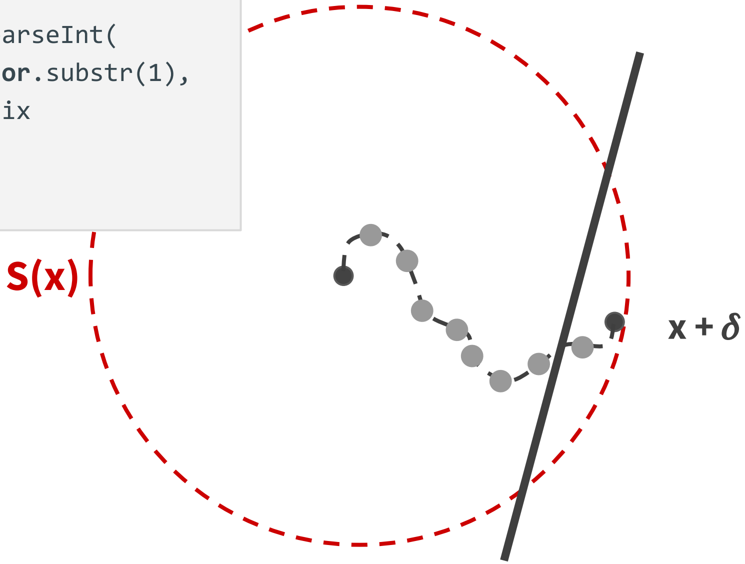
Solving the Inner max *loss* Efficiently

Gradient Based Optimization

$$\theta \leftarrow \theta - \nabla_{\delta}\, loss(\theta, \mathbf{x} + \delta, \mathbf{y})$$

$\delta \in \mathbf{S}(\mathbf{x})$

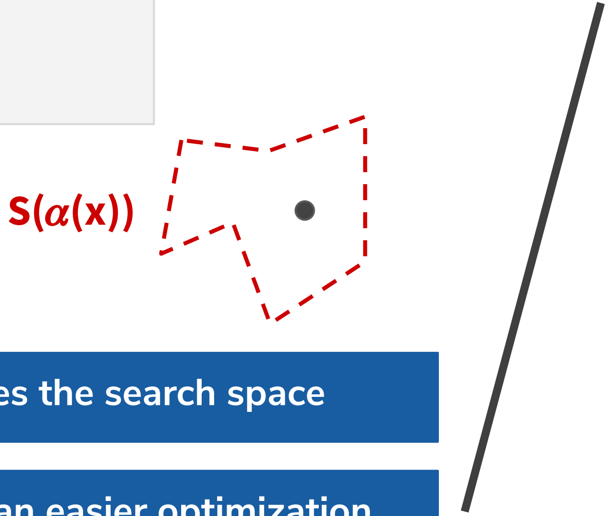
```
...
v = parseInt(
  color.substr(1),
  radix
)
...
```



Refine S

$$\min \left[\max_{\delta \in \mathbf{S}(\alpha(\mathbf{x}))} loss(\theta, \mathbf{x} + \delta, \mathbf{y}) \right]$$

```
parseInt(
  _,
  _
)
```



reduces the search space

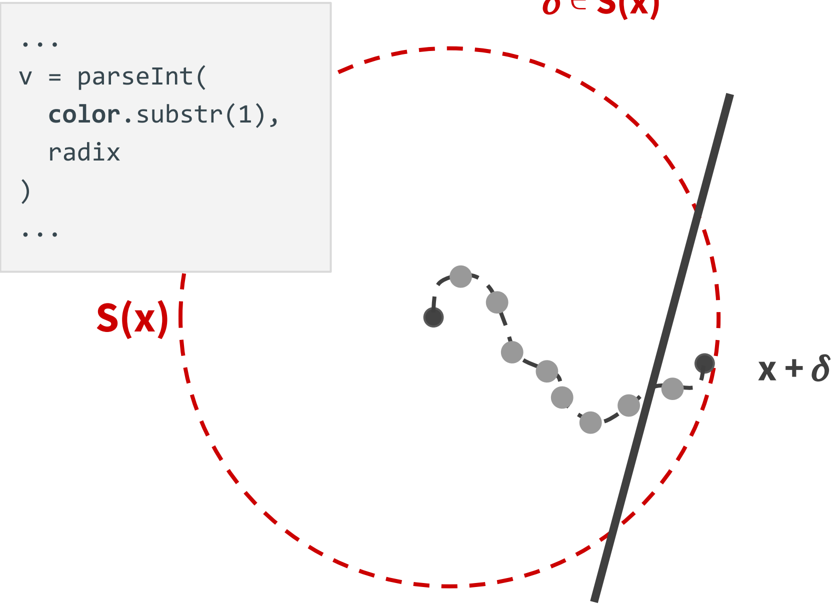
leads to an easier optimization

Solving the Inner max *loss* Efficiently

Gradient Based Optimization

$$\theta \leftarrow \theta - \nabla_{\delta}\, loss(\theta, \mathbf{x} + \delta, \mathbf{y})$$

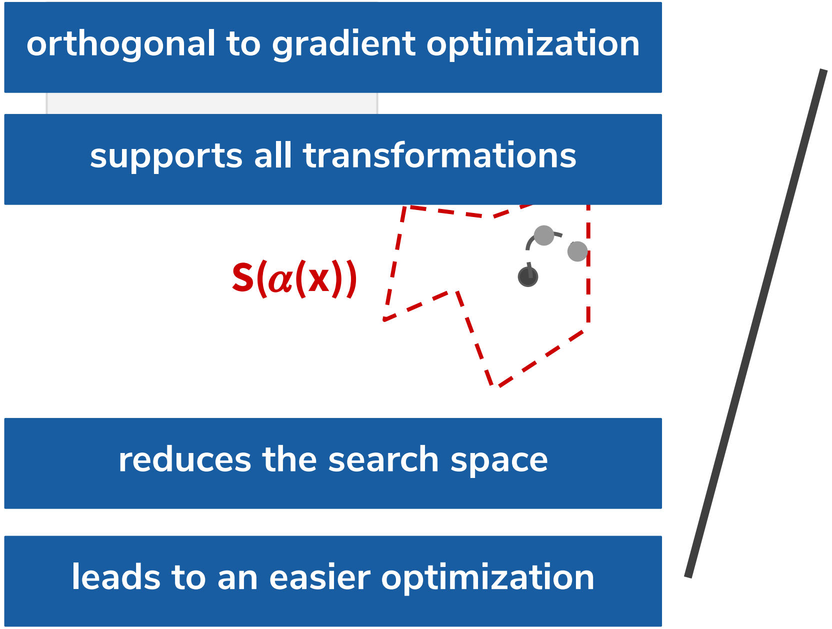
$$\delta \in \mathbf{S}(\mathbf{x})$$



```
...
v = parseInt(
  color.substr(1),
  radix
)
...
```

Refine S

$$\min\,[\max\limits_{\delta \in \mathbf{S}(\alpha(\mathbf{x}))} loss(\theta, \mathbf{x} + \delta, \mathbf{y})]$$



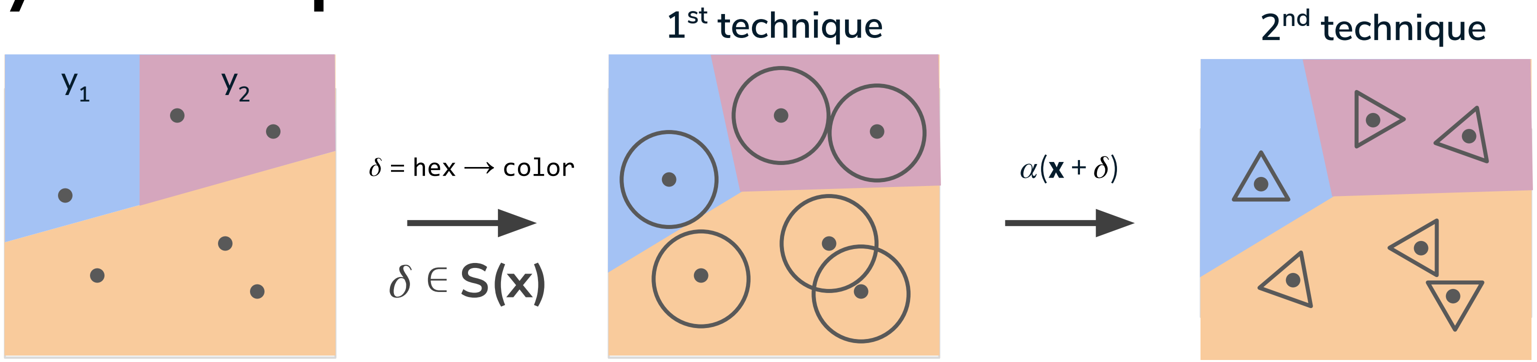
orthogonal to gradient optimization

supports all transformations

reduces the search space

leads to an easier optimization

Key Techniques



1st technique

2nd technique

δ = hex ⟶ color

$\delta \in \mathbf{S}(\mathbf{x})$

$\alpha(\mathbf{x} + \delta)$

Standard Training

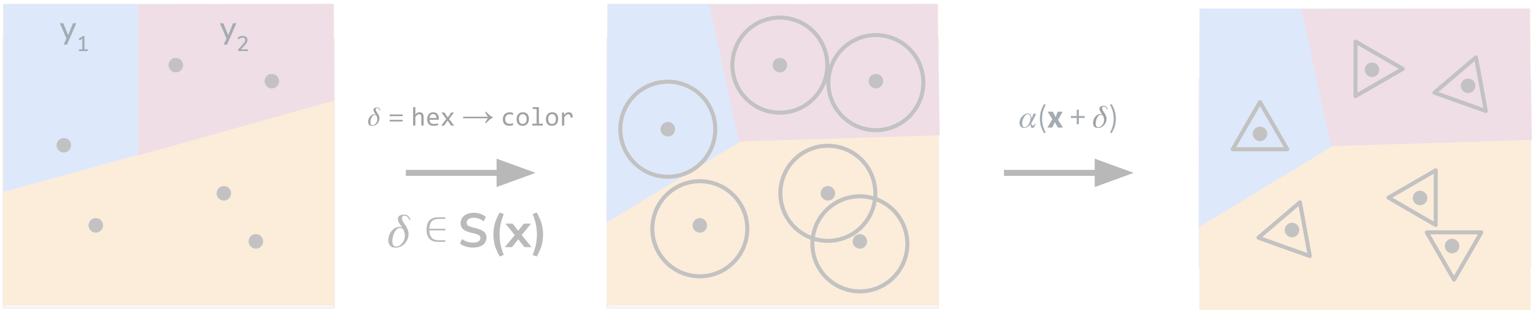
Adversarial Training

Representation Learning

Key Techniques

1st technique

2nd technique

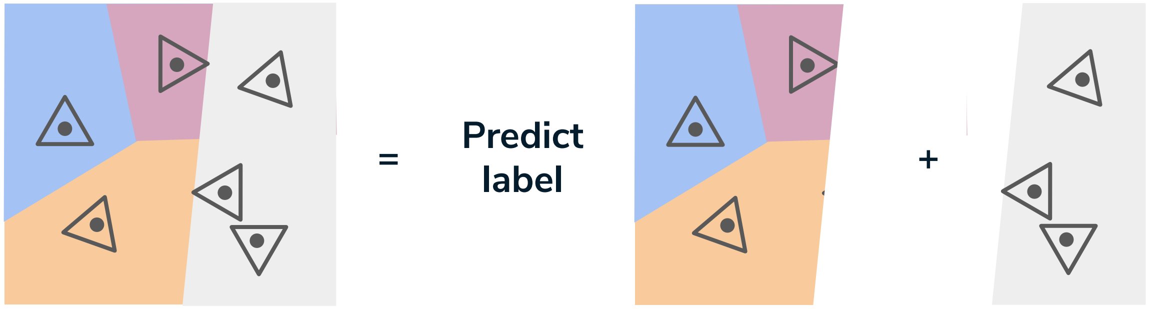

y_1
y_2
δ = hex ⟶ color
$\delta \in \mathbf{S}(\mathbf{x})$
$\alpha(\mathbf{x} + \delta)$

Standard Training

Adversarial Training

Representation Learning

3rd technique



Abstain

Robust & Accurate

Robust

Robustness of Existing Models

Type Inference [1]

89%
accuracy

45%
robustness

Adversarial training

57%
robustness

+
Refinement & Abstain

67%
robustness

Code Captioning [2,3]

39.2
F1

19.6
robust F1

27.5
robust F1

Malware Detection [4]

99%
accuracy

~2%
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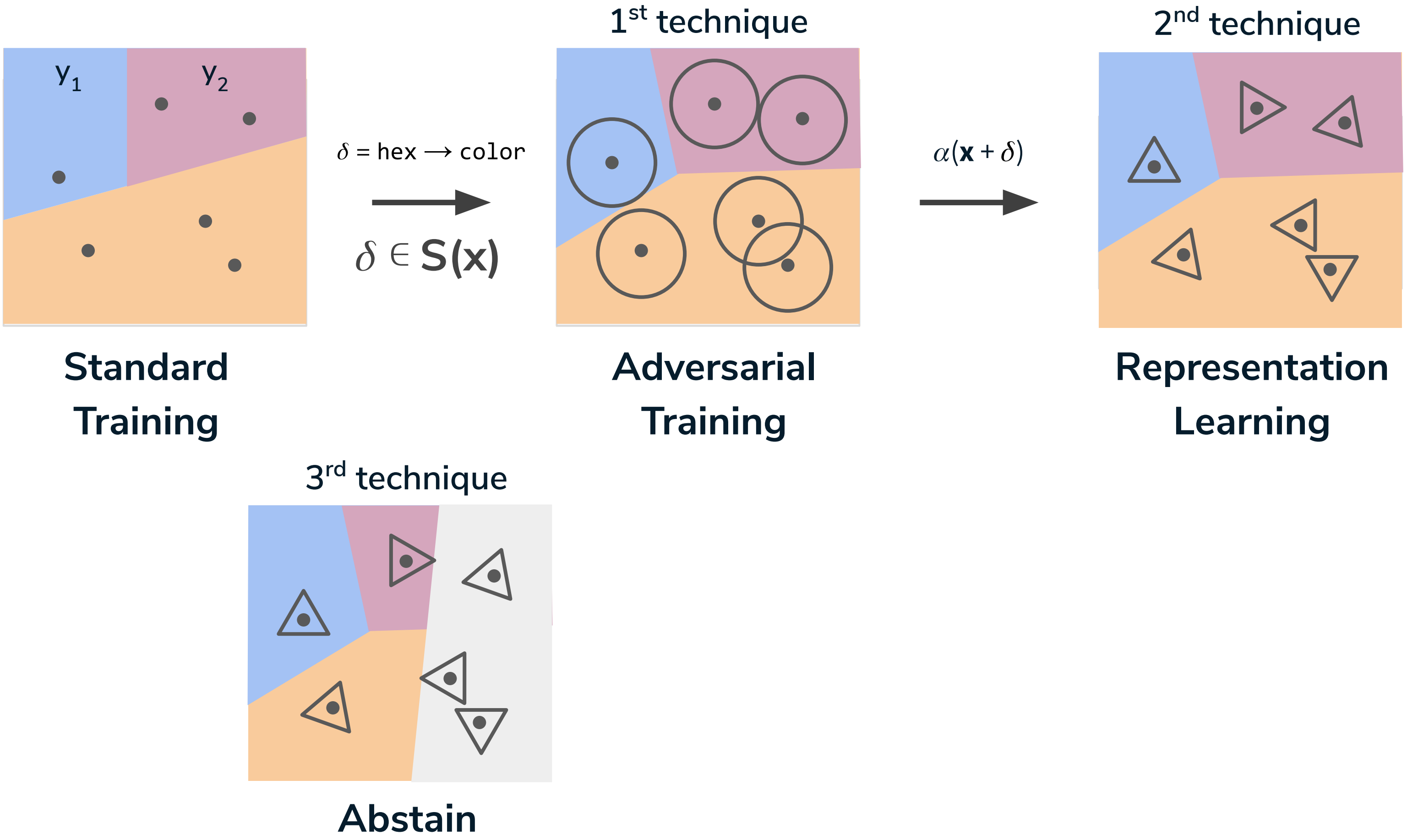
too expensive

Robust Models for Source Code



Standard Training

δ = hex ⟶ color

$\delta \in \mathbf{S(x)}$

1st technique

Adversarial Training

$\alpha(\mathbf{x} + \delta)$

2nd technique

Representation Learning

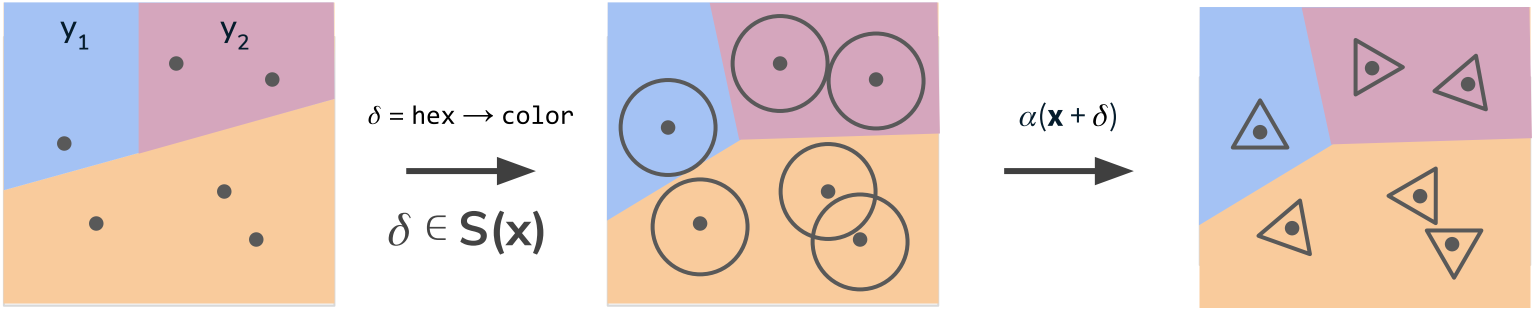
3rd technique

Abstain

Robust Models for Source Code

1st technique

2nd technique

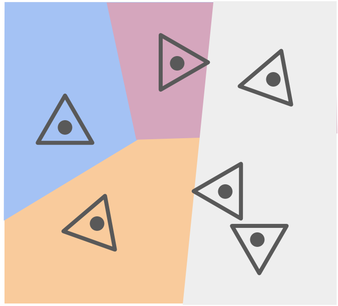


Standard Training

Adversarial Training

Representation Learning

3rd technique



Abstain

Next technique?

pre-processing

compositionality

normalization