Implementing GANs

Duke MLSS

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Probability Distributions

$$x \sim p(x)$$

x "is drawn from" $p(x)$

x "is a sample from" $p(x)$

p(x) a distribution assigning 50% probability to H, 50% to T

x a random variable, equal to H or T

Probability Distributions

$$x \sim p(x)$$

x "is drawn from" $p(x)$

x "is a sample from" $p(x)$

p(x) a distribution assigning some small probability to each possible setting of pixel values in a 24-bit-color 100x100 image.

x a random variable, equal to some 100x100 image.

Generative modeling

Approximate $p(x)$ that generated the data

Do we want to…

- evaluate relative likelihoods of different data points?
- compute conditional distributions?
- do inference on latent variables?
- produce new samples (perhaps conditioned on something)?

Note: we have no "labeled" $p(x)$ values, just lots of x

Generative modeling

For today:

Generate New Samples

(create “realistic” images, sounds, etc.)

Sampling

How do we generate a sample from a distribution?

Method 1: Go out and flip a coin.
(slow, expensive)

p(x) a distribution assigning 50% probability to H, 50% to T

x a random variable, equal to H or T

Sampling

How do we generate a sample from a distribution?

Method 2: *Simulate* a sample.

```
def G(z):
  if z > 0.5:
    return "Heads"
  else:
    return "Tails"
```

`np.random.uniform(0,1)`

Source of (pseudo-)randomness

Deterministic mapping

Sample from p(x)

Sampling

But sometimes, we don't know exactly what G(z) should be.

Sampling

But sometimes, we don't know exactly what G(z) should be.
We can estimate *parameters* from *data*.

```
def G(z):
  if z > theta:
    return "Heads"
  else:
    return "Tails"
```

`np.random.uniform(0,1)`

Source of (pseudo-)randomness

Deterministic mapping

Sample from p(x)

Sampling

How do we generate a sample from a distribution?

Method 1: Go out and take a picture.
(slow, expensive)

p(x) a distribution assigning some small probability to each possible setting of pixel values in a 24-bit-color 100x100 image.

x a random variable, equal to some 100x100 image.

Sampling

How do we generate a sample from a distribution?

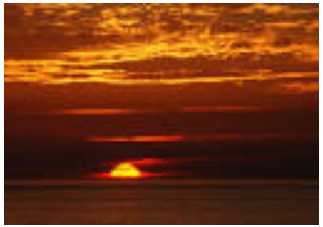
Method 2: *Simulate* a sample.

```
def G(z):
  # hmmmm…
  # help?
```

`np.random.uniform(0,1)`

Source of (pseudo-)randomness

Deterministic mapping



Sample from p(x)

How to write **G**?

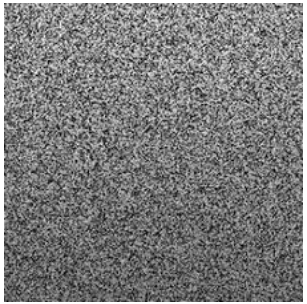
It's just a function: learn it!

```
np.random.uniform(0,1)
```

Source of (pseudo-)randomness

```
def G(z):
  return MLP(z, theta)
```

Deterministic mapping with randomly initialized parameters



Sample from p(x)

Learn **G**

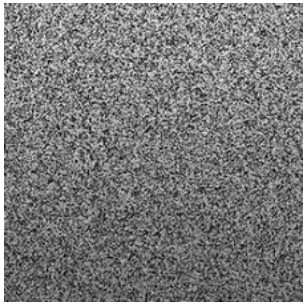
But with what loss function?

```
np.random.uniform(0,1)
```

Source of (pseudo-)randomness

```
def G(z):
  return MLP(z, theta)
```

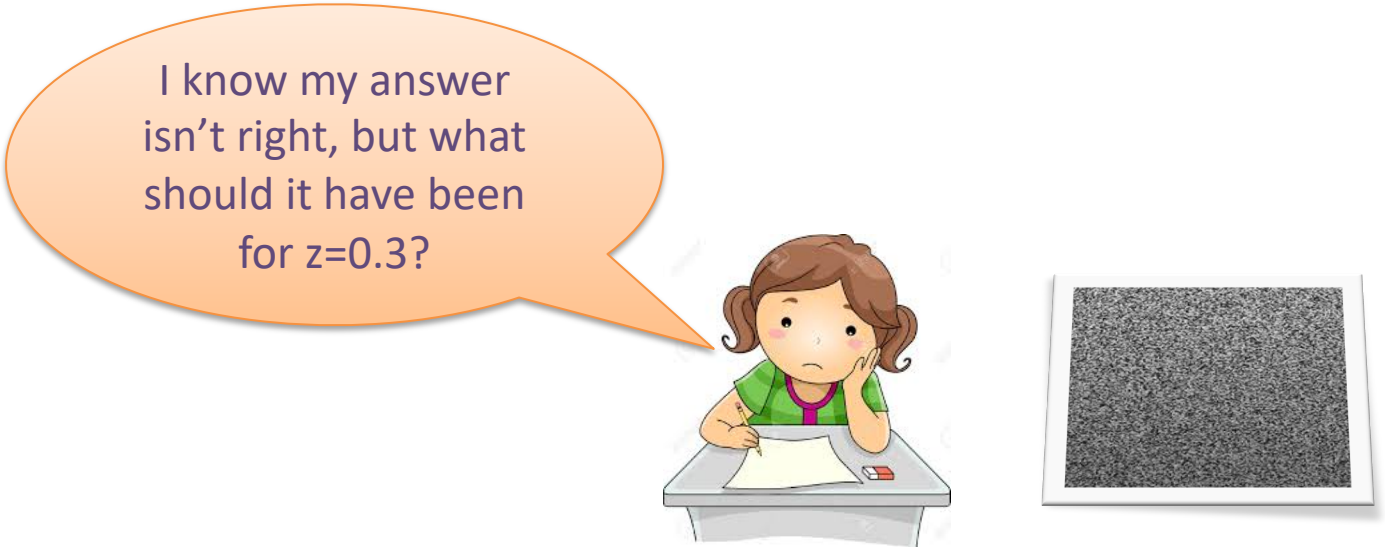
Deterministic mapping with randomly initialized parameters



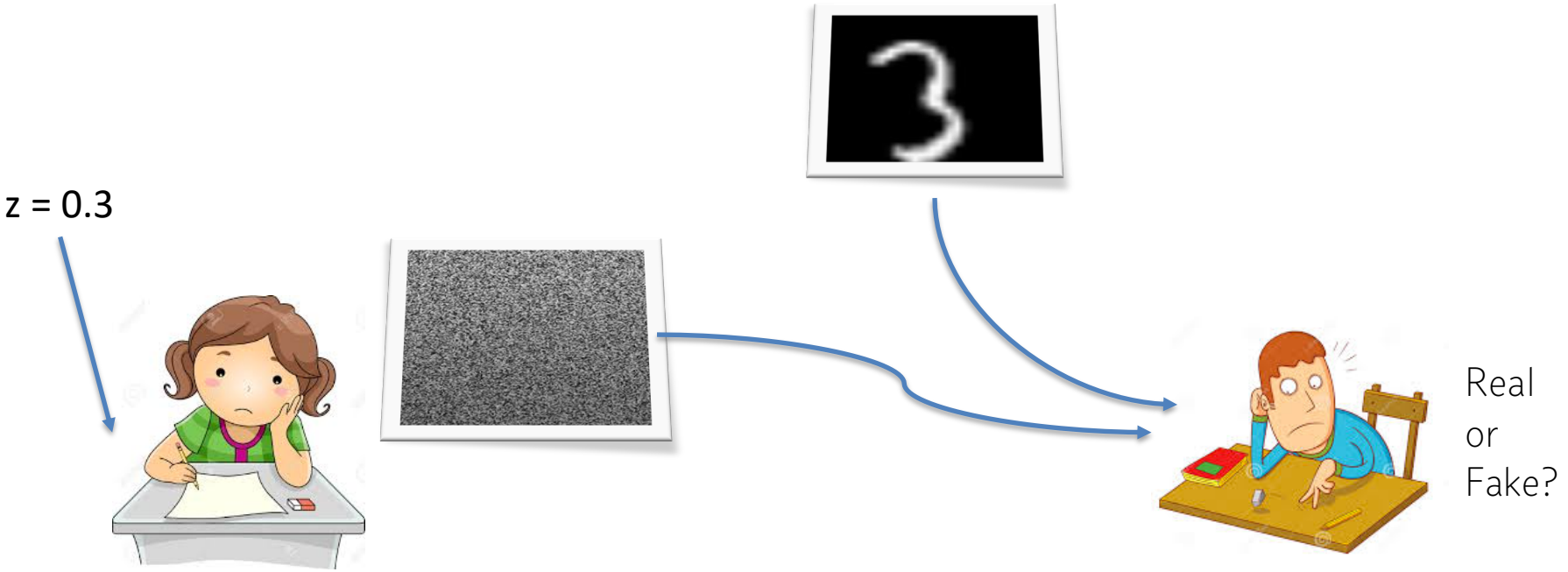
Sample from p(x)

Learn **G**

How do you teach **G** with no (in, out) examples?



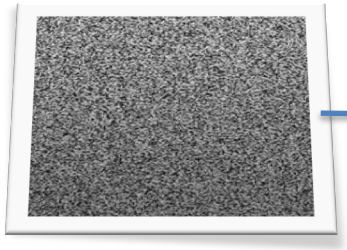
Get two students (neural networks)



Get two students (neural networks)

real

fake

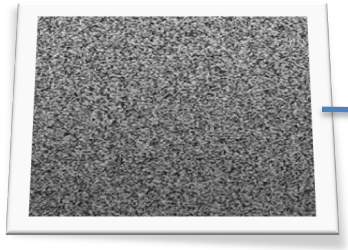


Ohhh. So if the top left three pixels are black, it's **real**. Otherwise, **fake**.

Got two students (neural networks)

You're failing to fool the discriminator. Try making the top left pixels darker.

z = 0.3

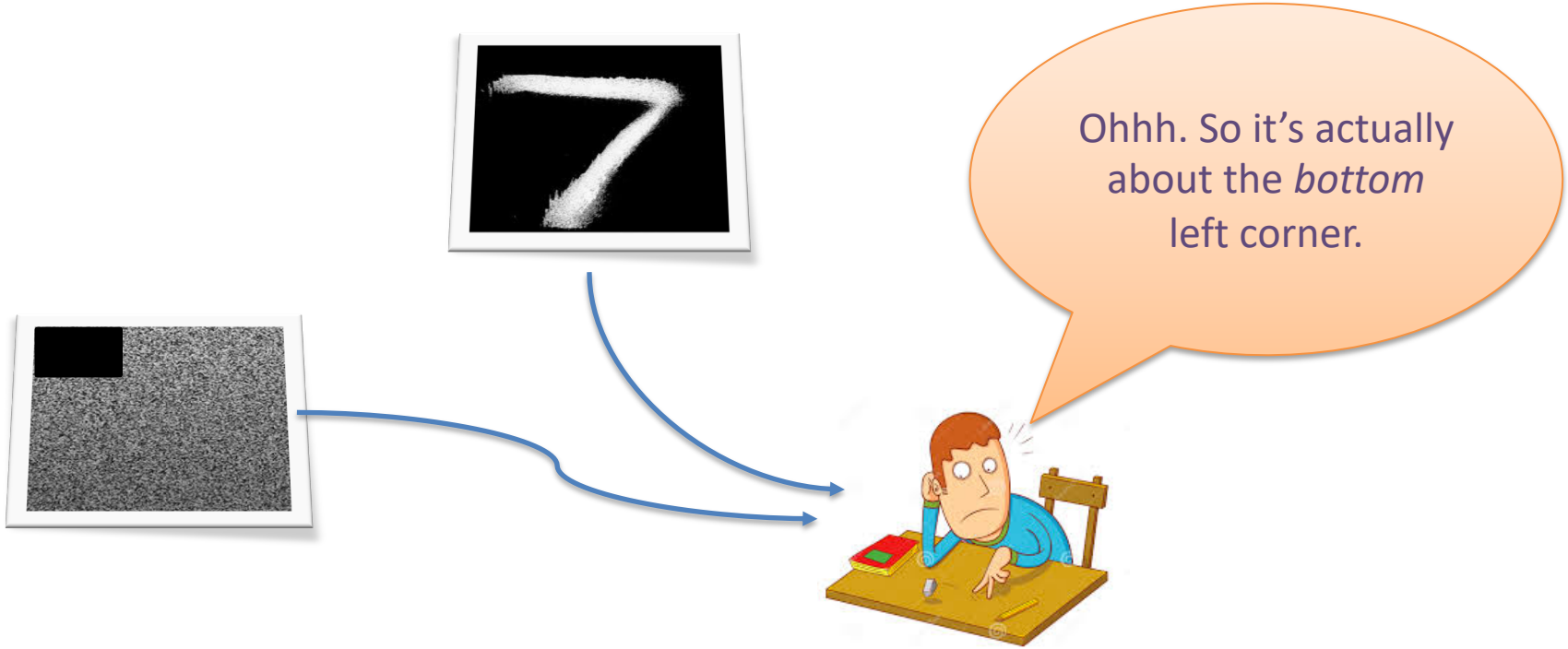


Get two students (neural networks)

You're failing to fool the discriminator. Try making the top left pixels darker.

z = 0.5

Get two students (neural networks)



Many iterations later…

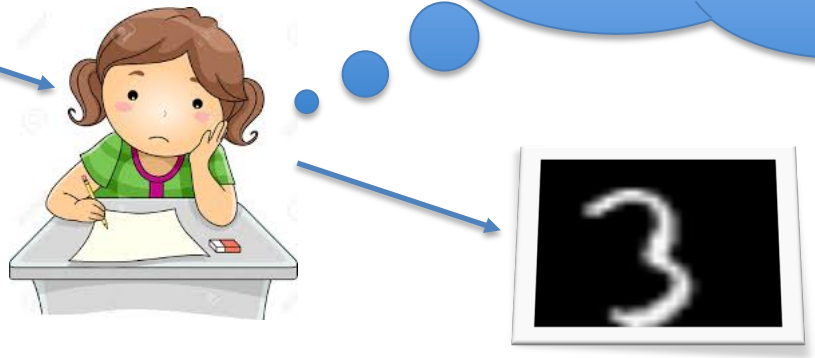
z = 0.7

I'm stumped.

The importance of *z*

I'm not very creative. I'm just an MLP. Same input in, same output out.

z = 0.7

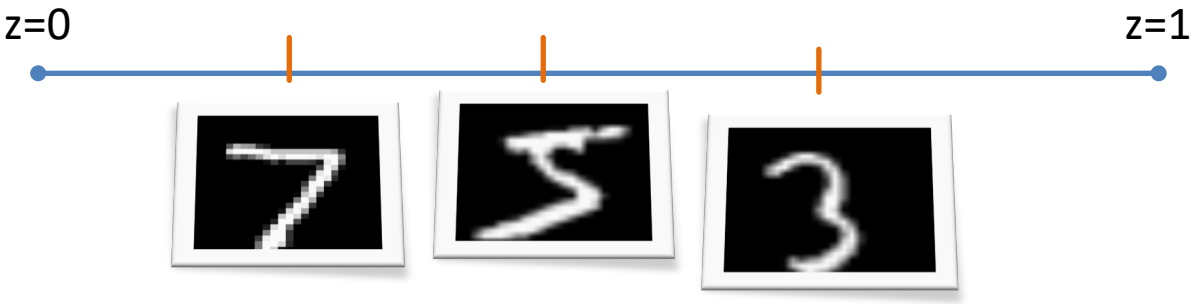


The importance of *z*

I'm not very creative. I'm just an MLP. Same input in, same output out.

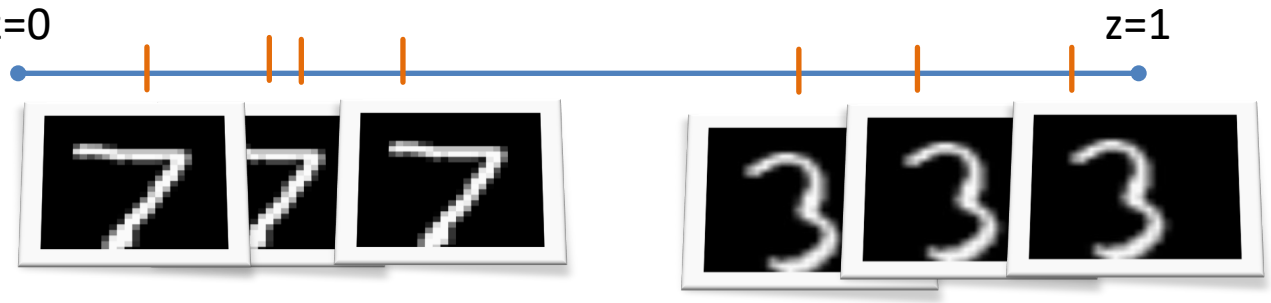
z = 0.213

The importance of *z*



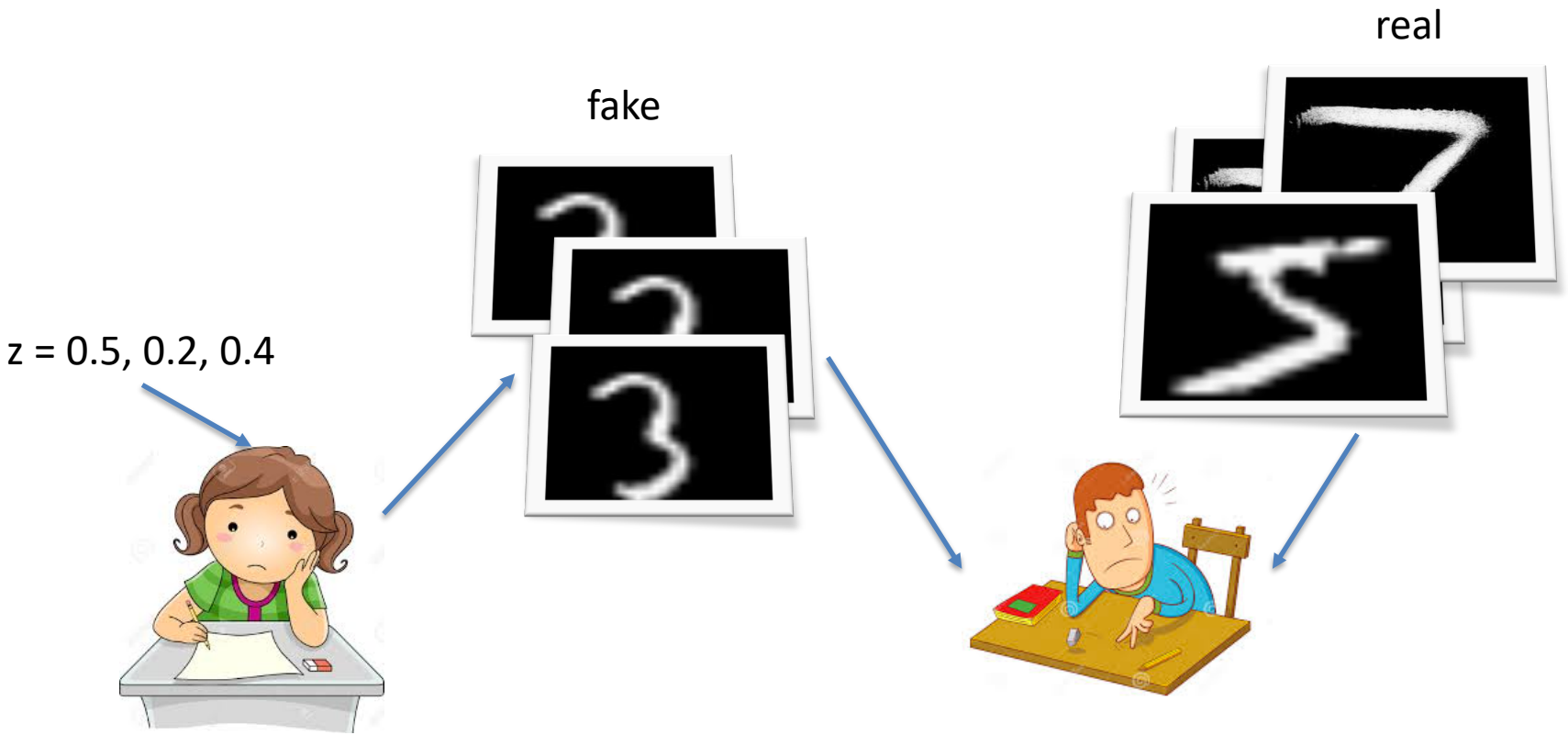
G a *deterministic function* from *z* to images

The importance of *z*

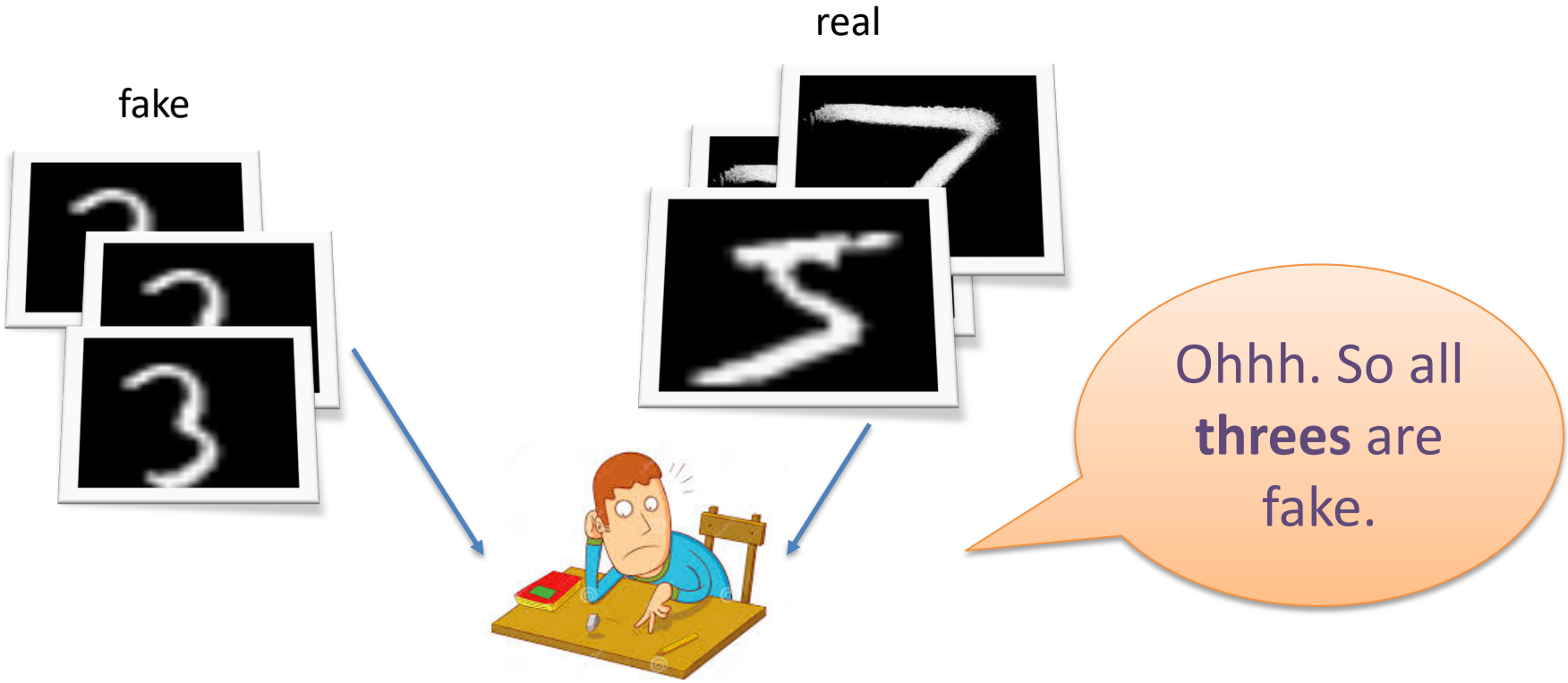


What if G learns to "play it safe" and always generate similar images?

What if G always writes the same thing?

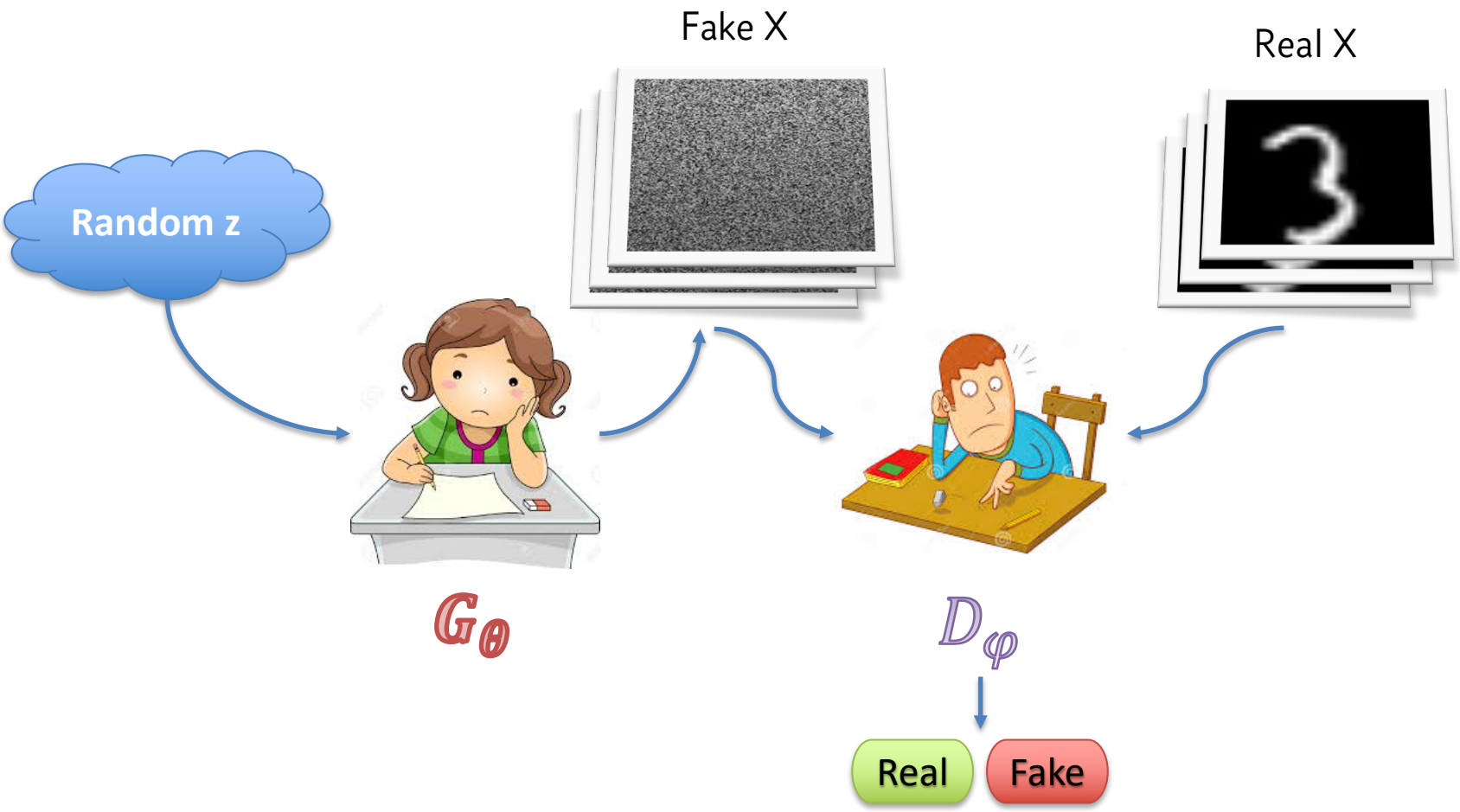


What if G always writes the same thing?



Main takeaway

We don’t know how to teach G to draw. But with two students, we can make them teach each other!


Fake X
Real X
Random z
G_θ
D_φ
Real
Fake

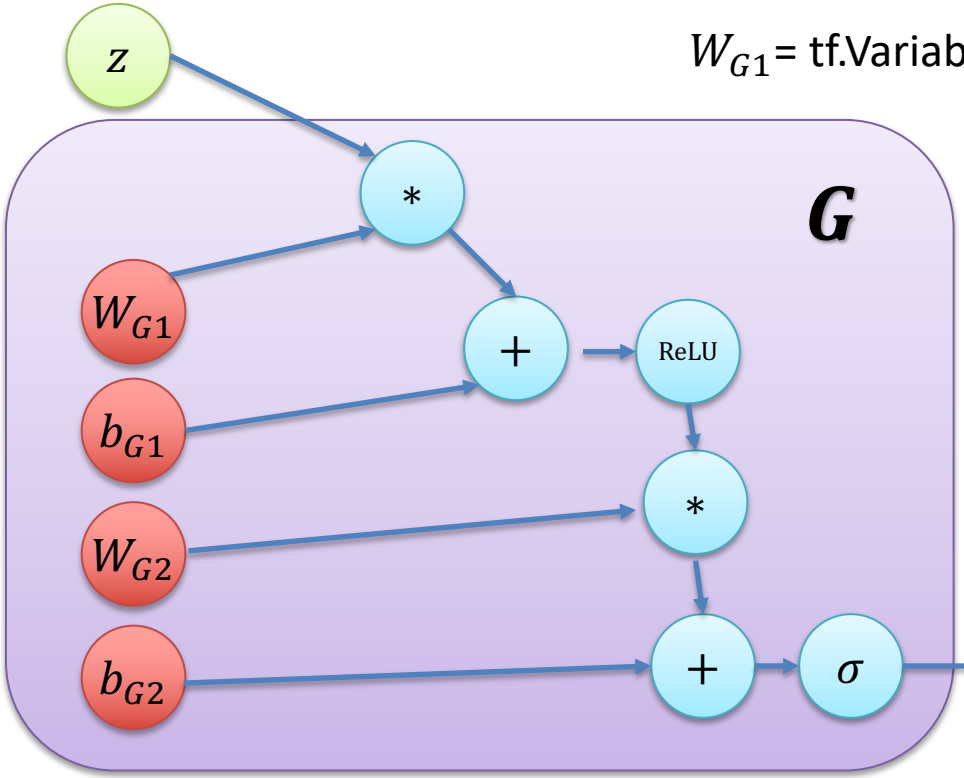
Implementation subtleties

z = tf.placeholder([50, 20])

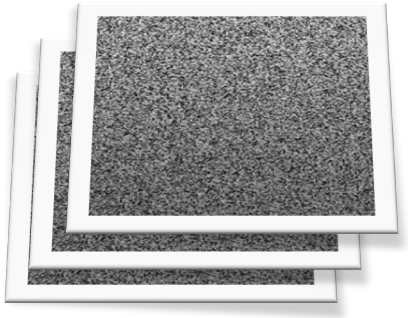
- We provide *multiple* random numbers (say, 20) to inform G in creating *each* image.
- We ask G to create a whole “batch” (say, 50) of fake images each batch.

Architecture of $\boldsymbol{G}$: 20 → 256 → 784

W_{G1} = tf.Variable(tf.truncated_normal([20, 256], stddev=0.1)



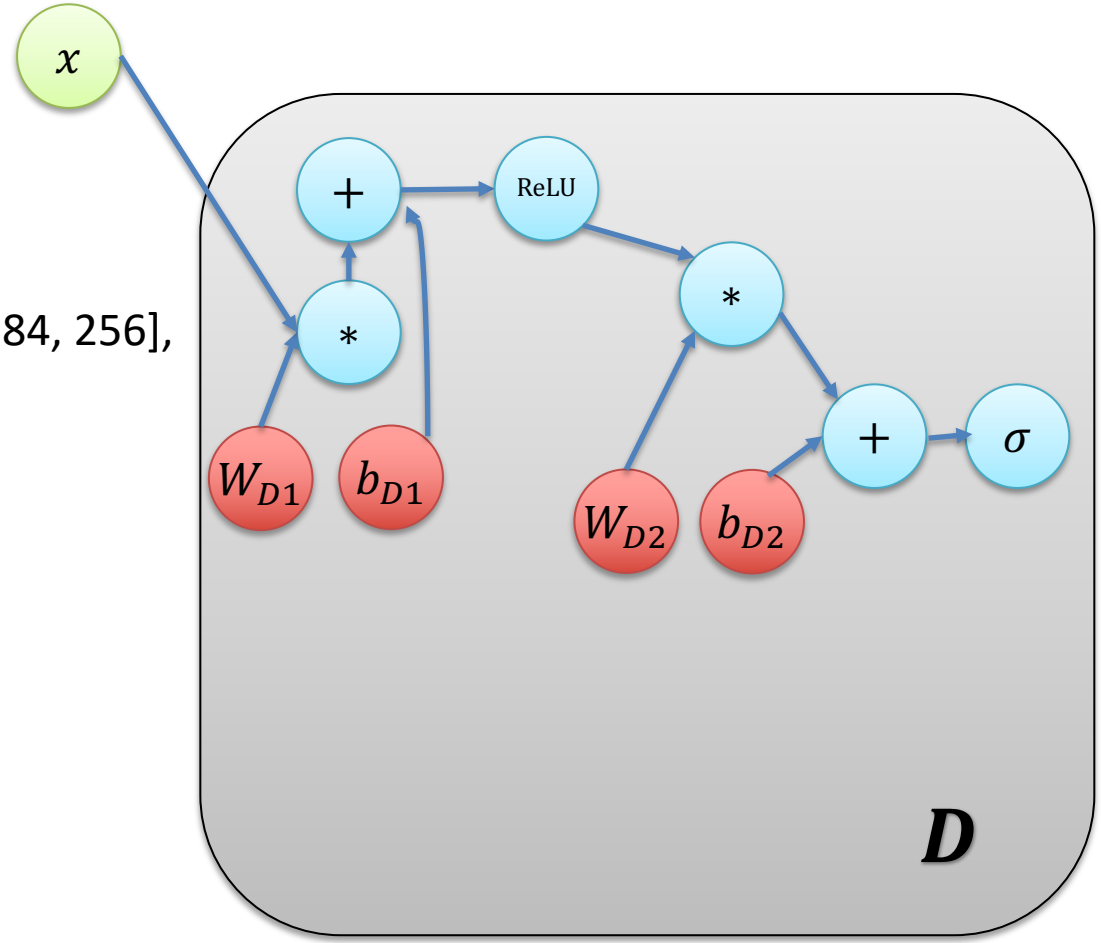
Our output: values between 0 and 1 (black and white) for each pixel.

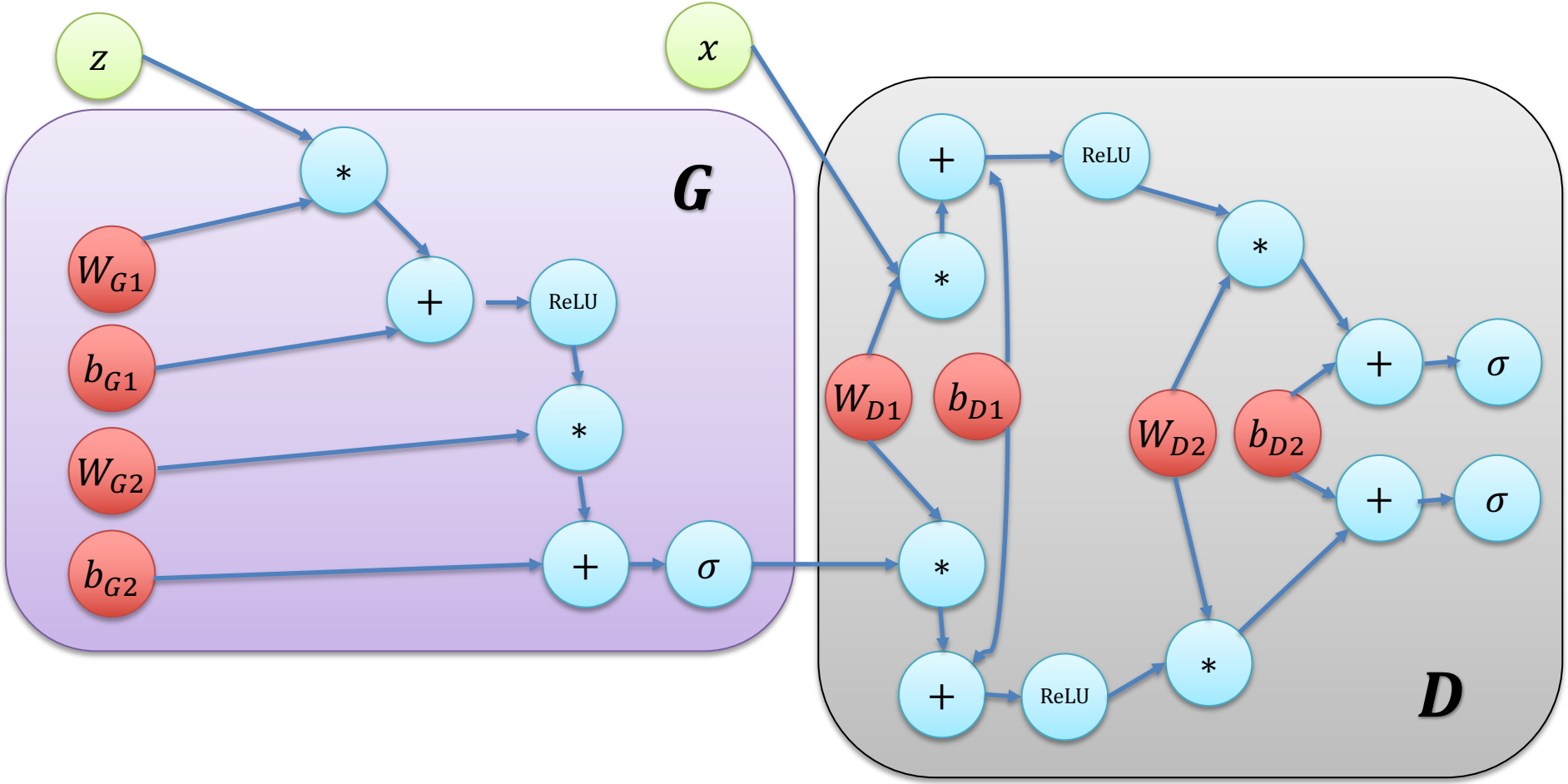


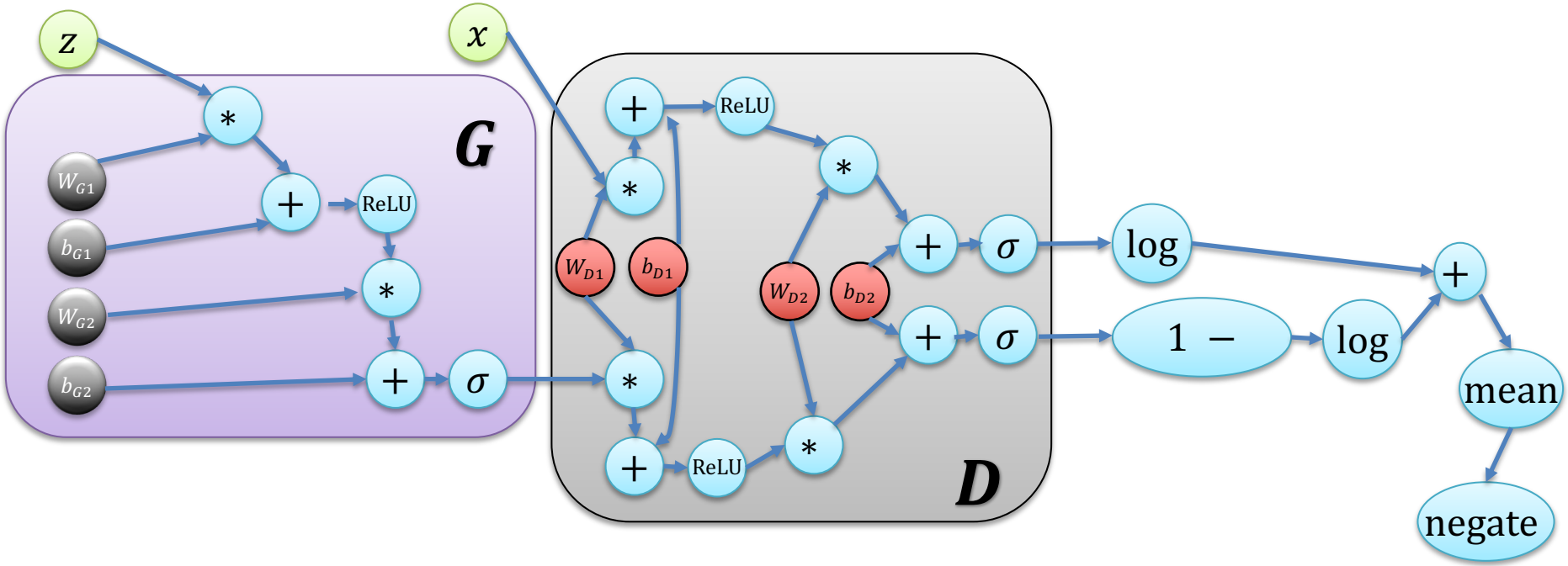
Architecture of **D**:

784 → 256 → 1

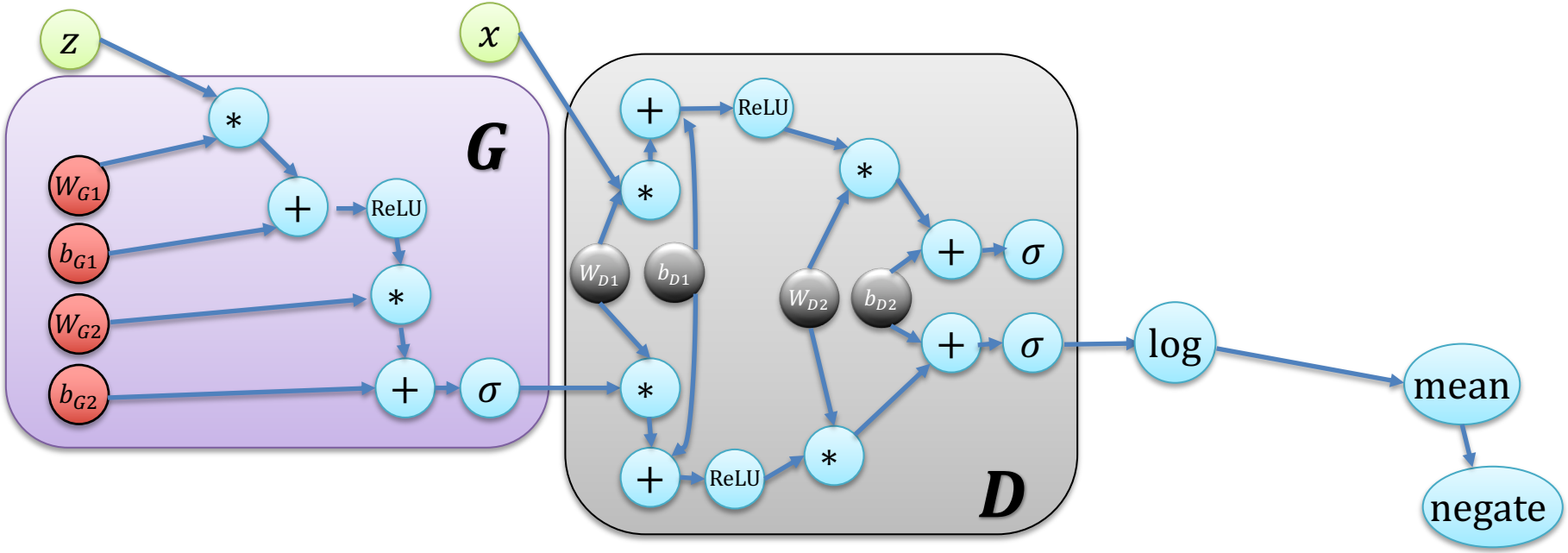
W_{D1}= tf.Variable(tf.truncated_normal([784, 256], stddev=0.1)



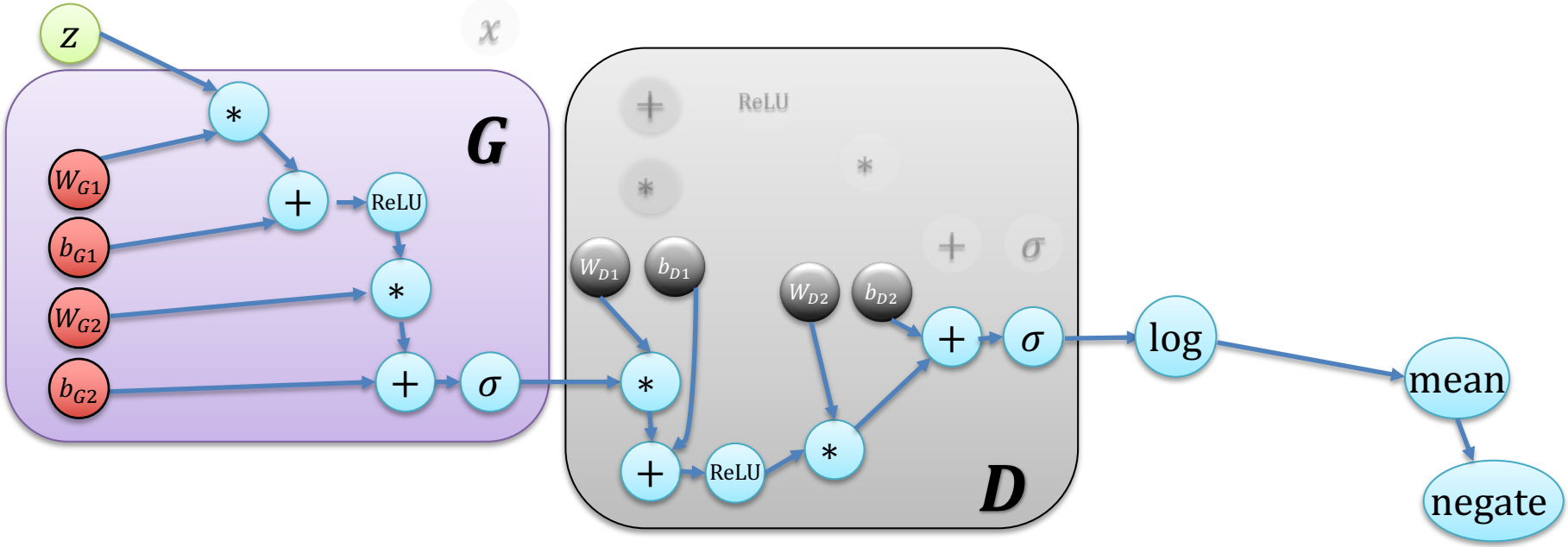

z
x
G
D
*
+
ReLU
W_{G1}
b_{G1}
W_{G2}
b_{G2}
σ
W_{D1}
b_{D1}
W_{D2}
b_{D2}



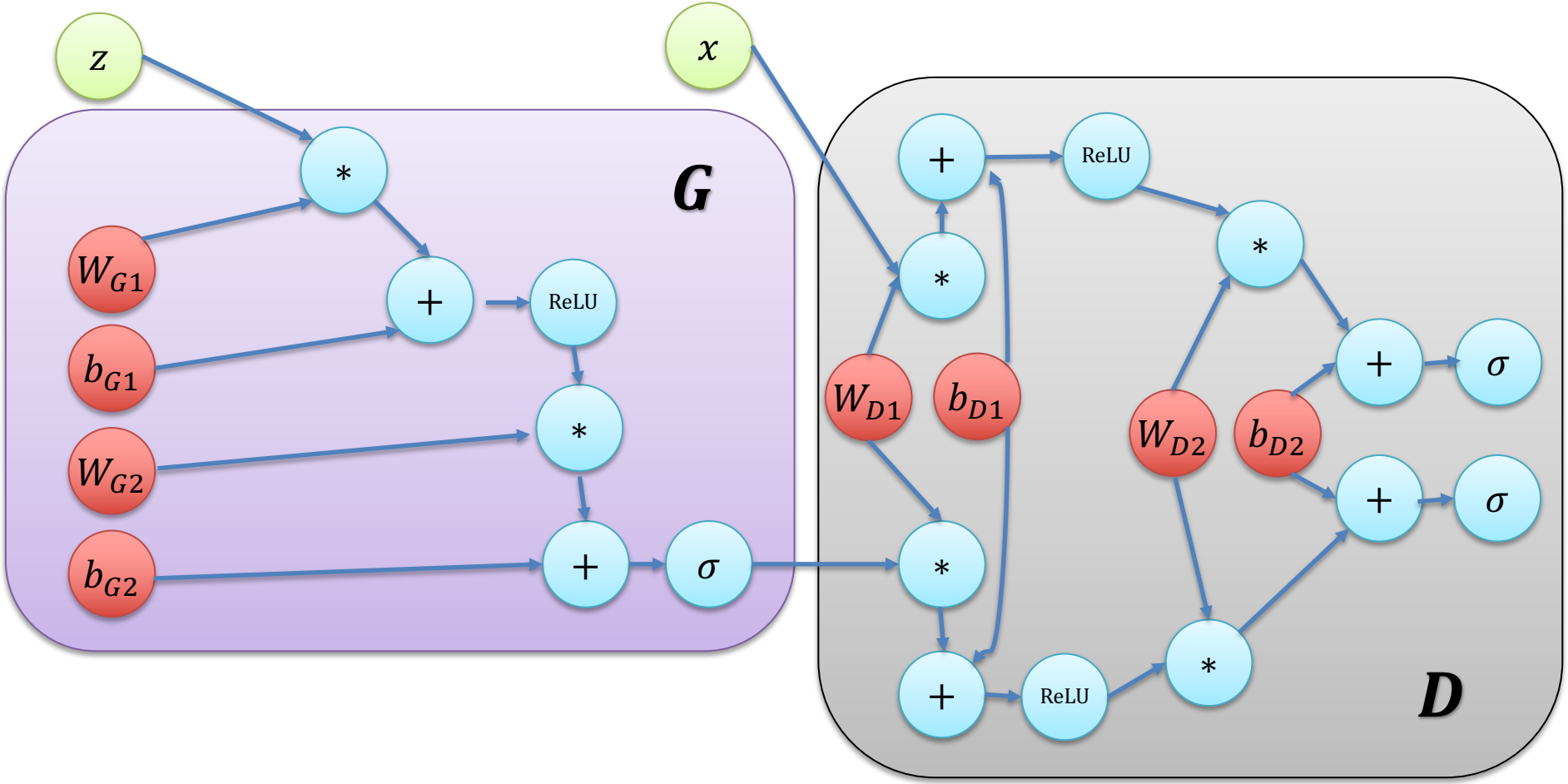
Loss when training D



Loss when training G



Loss when training G


z
x
G
D
*
+
ReLU
W_{G1}
b_{G1}
W_{G2}
b_{G2}
σ
W_{D1}
b_{D1}
W_{D2}
b_{D2}