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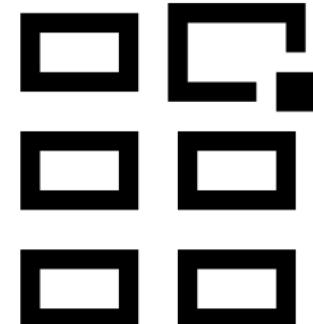


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# Conditional Generation: Intuition

# Outline

- Unconditional generation
- Conditional vs. unconditional generation



# Unconditional Generation

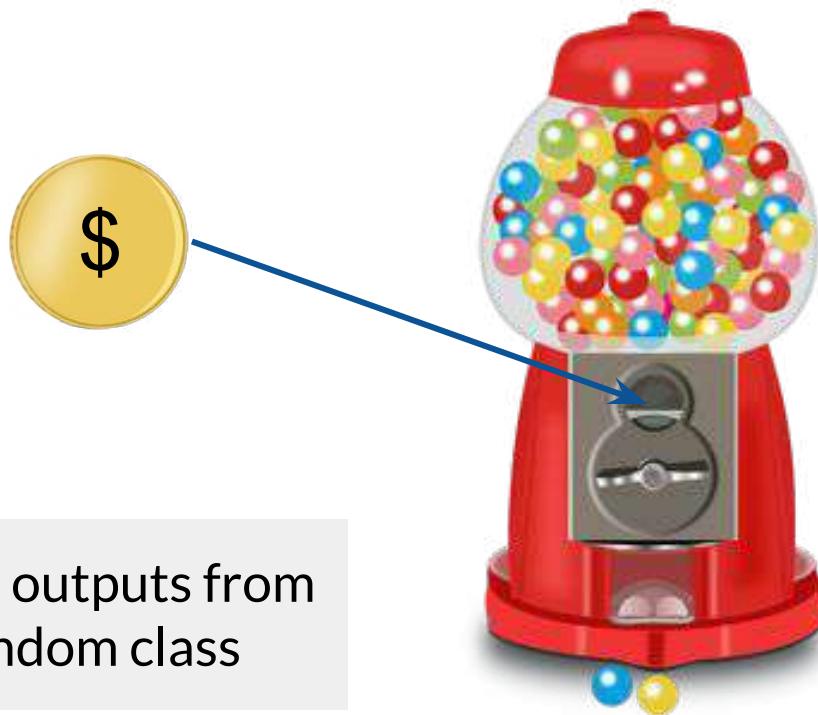
You get outputs from  
a random class

# Unconditional Generation



You get outputs from  
a random class

# Unconditional Generation



You get outputs from  
a random class

# Unconditional Generation



# Unconditional Generation



You get outputs from  
a random class

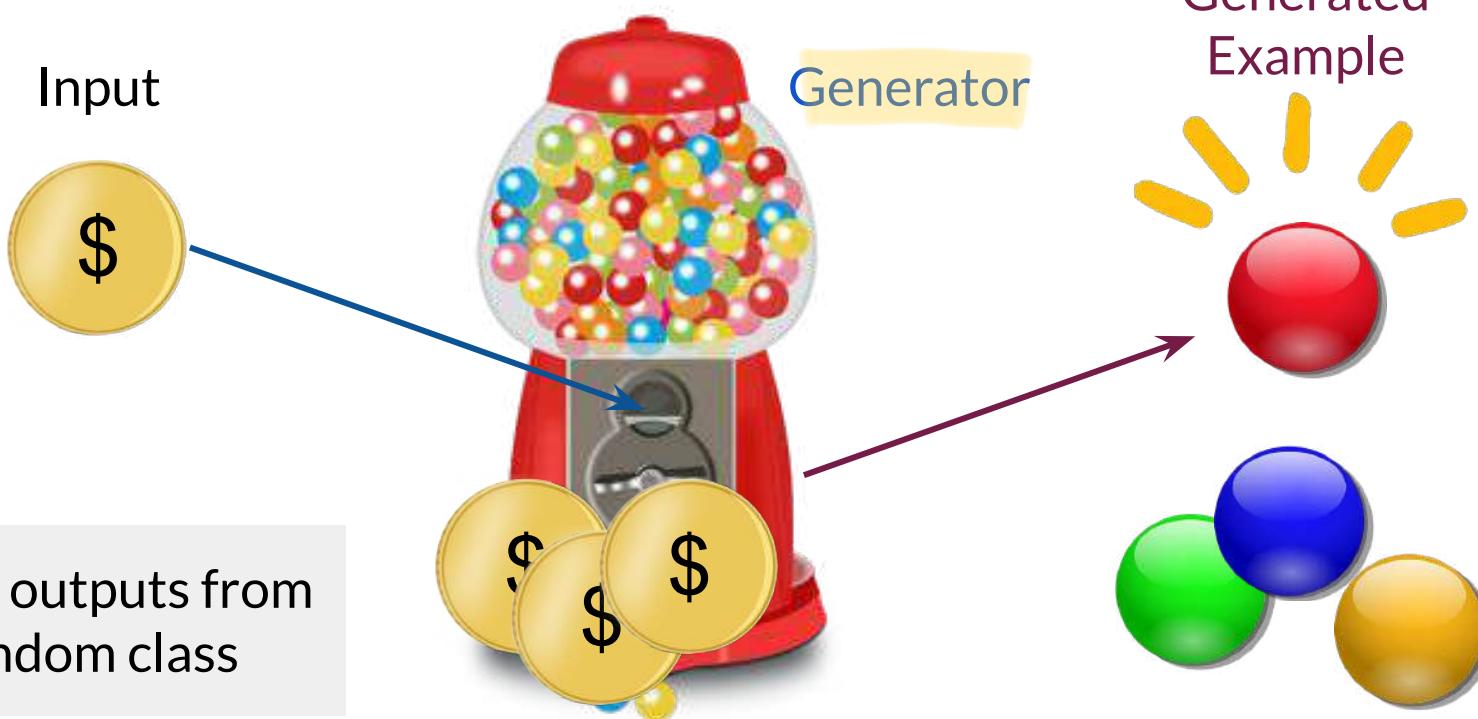
# Unconditional Generation



# Unconditional Generation



# Unconditional Generation



# Conditional Generation

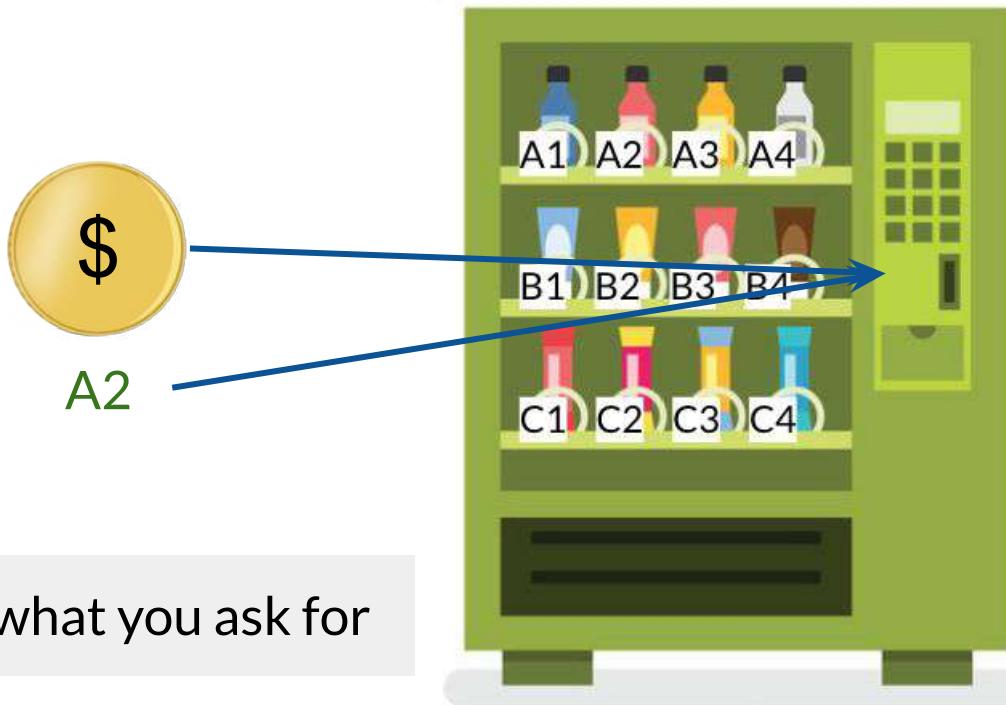
You get what you ask for

# Conditional Generation



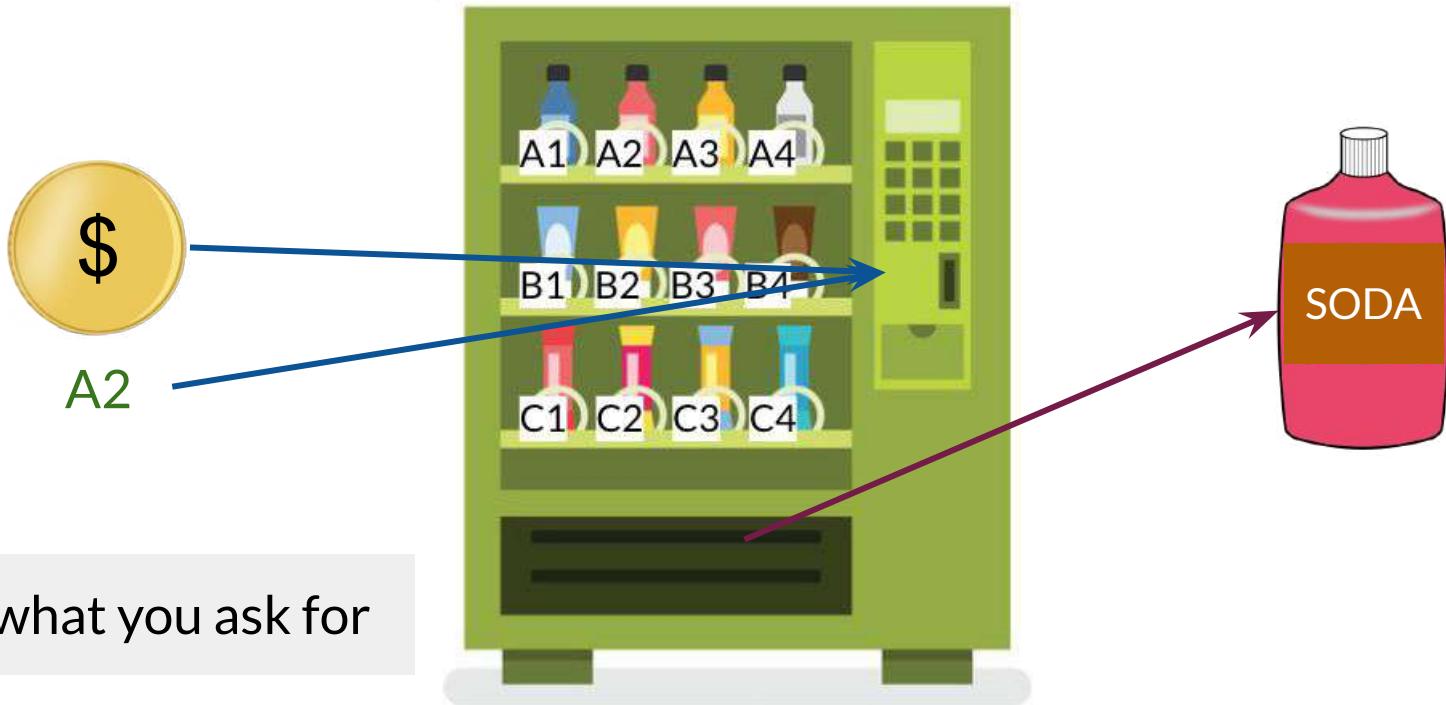
You get what you ask for

# Conditional Generation



You get what you ask for

# Conditional Generation



You get what you ask for

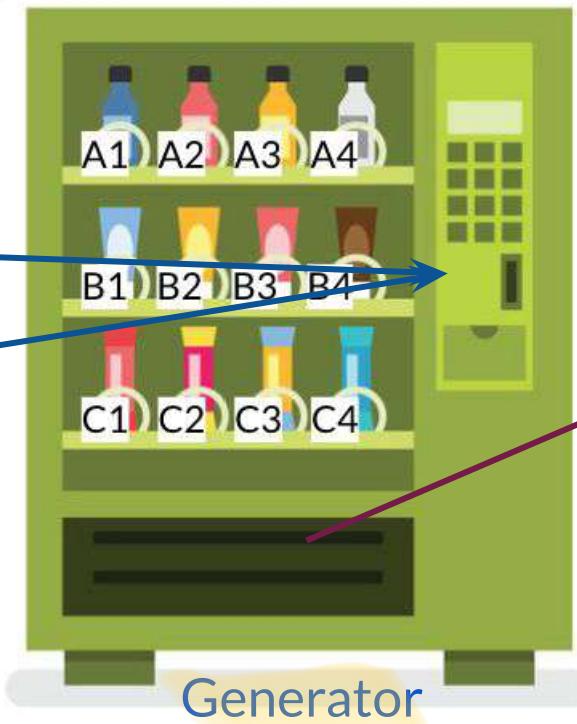
# Conditional Generation

Input



Class A2

You get what you ask for  
*(For a specific class)*



Still random  
but within that class

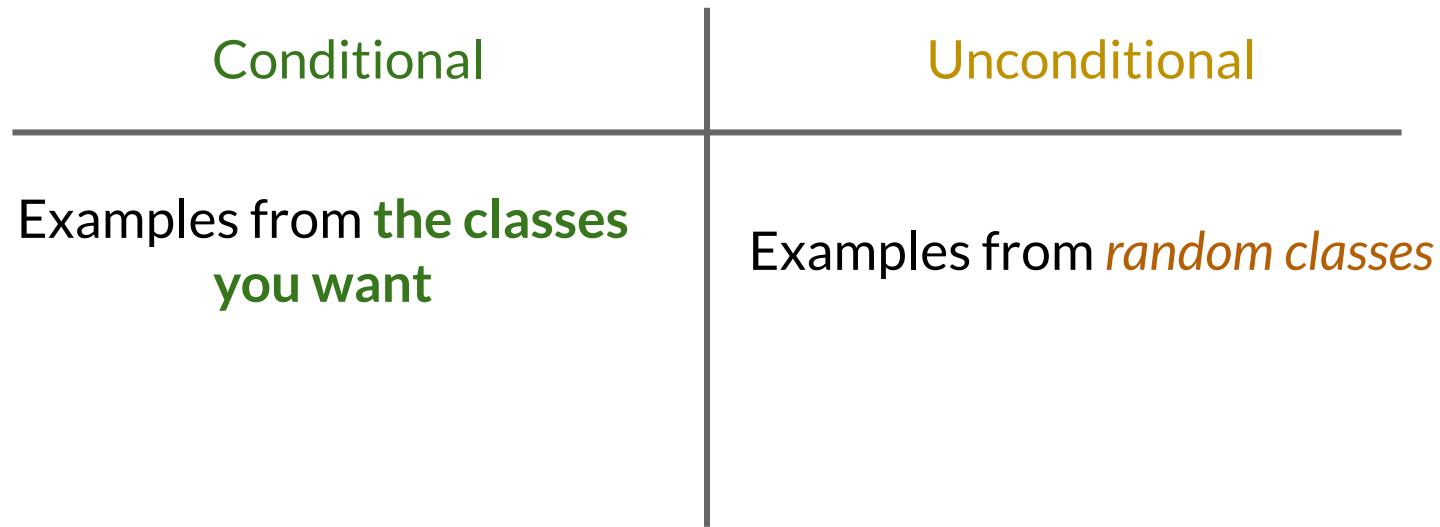


Generated Example

# Conditional vs. Unconditional Generation



# Conditional vs. Unconditional Generation

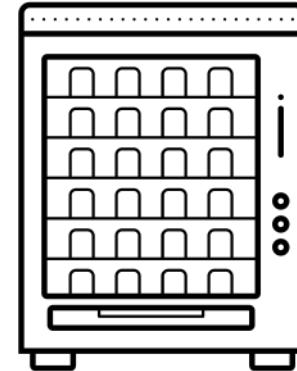


# Conditional vs. Unconditional Generation

Conditional	Unconditional
Examples from <b>the classes you want</b>	Examples from <b>random classes</b>
Training dataset needs to be <b>labeled</b>	Training dataset <b>doesn't need to be labeled</b> <i>prew labs/ass</i>

# Summary

- Conditional generation requires labeled datasets
- Examples can be generated for the selected class





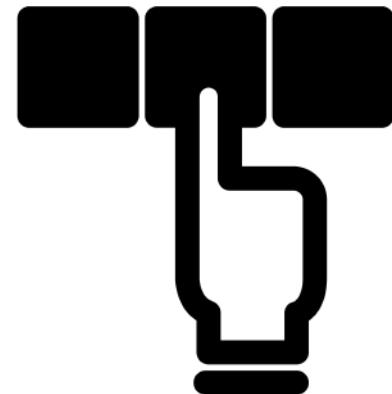
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# Conditional Generation: Inputs

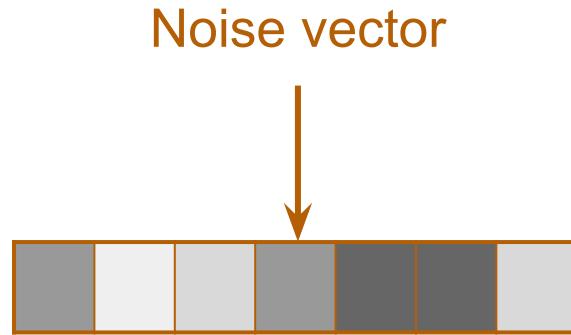
# Outline

- How to tell the generator what type of example to produce
- Input representation for the discriminator

labeled dataset ↗  
genor  
discrim

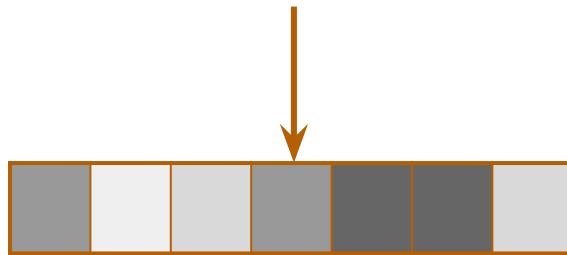


# Generator Input

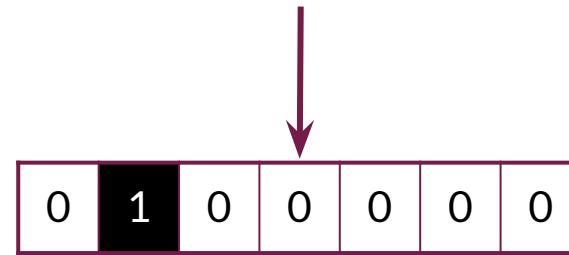


# Generator Input

Noise vector

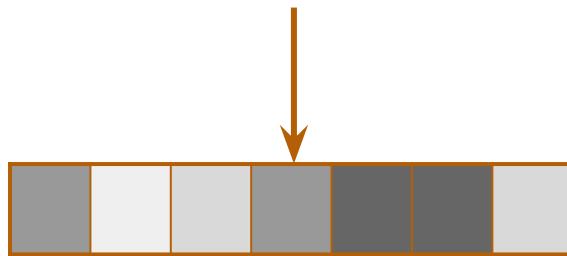


Class (one-hot) vector

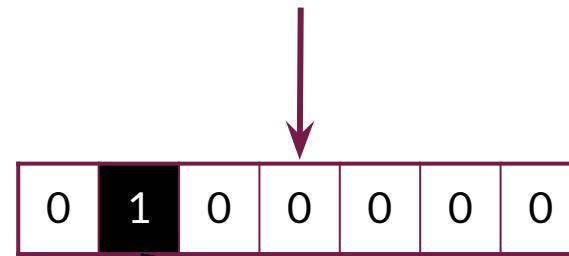


# Generator Input

Noise vector



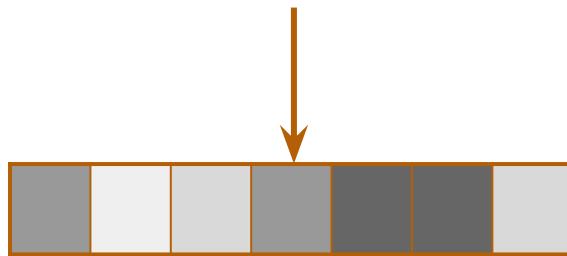
Class (one-hot) vector



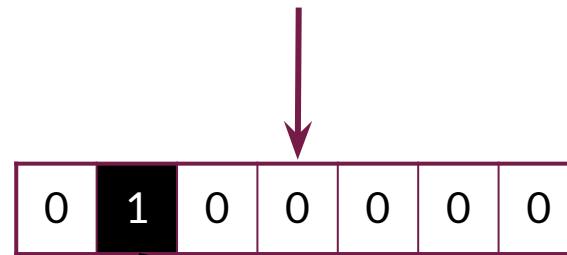
Husky

# Generator Input

Noise vector



Class (one-hot) vector

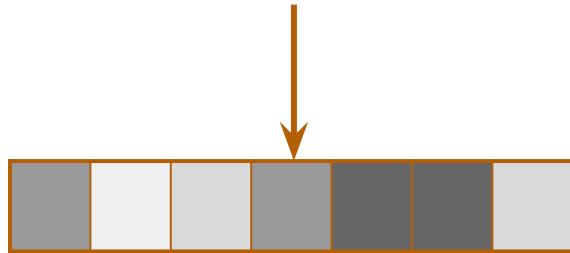


Randomness in the  
generation

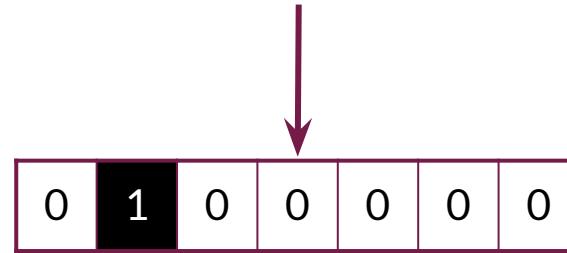
# Generator Input

*before we only had this*

Noise vector +



Class (one-hot) vector



Randomness in the  
generation

*but in Husky class*

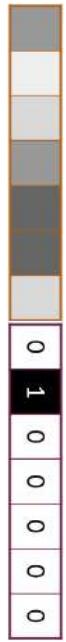
Control in the  
generation

# Generator Input

in one vector

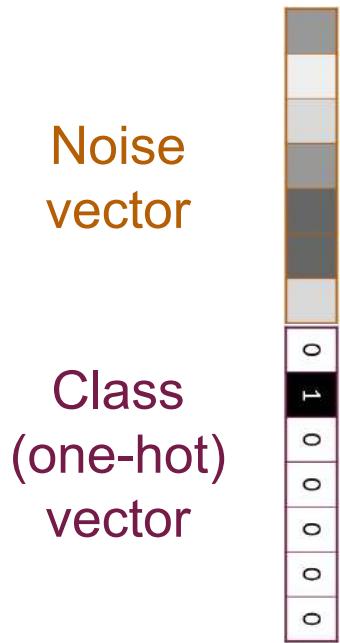
Noise vector

Class (one-hot) vector



Husky

# Generator Input



Generator

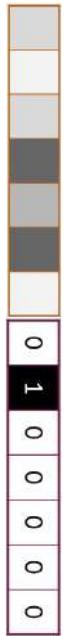
Husky

Output



# Generator Input

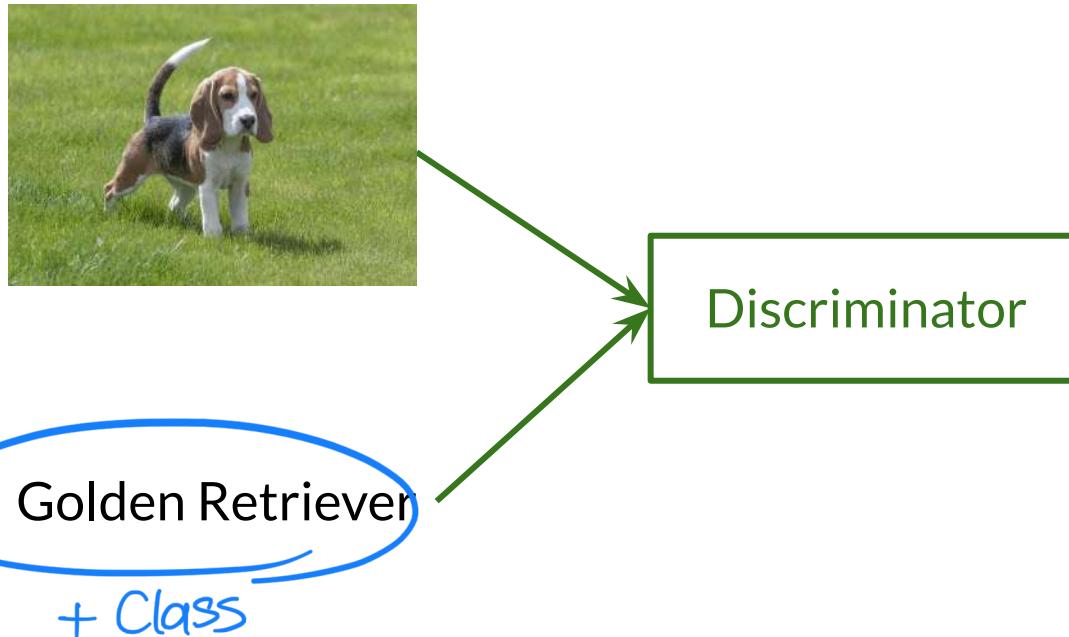
Noise vector  
Class (one-hot) vector



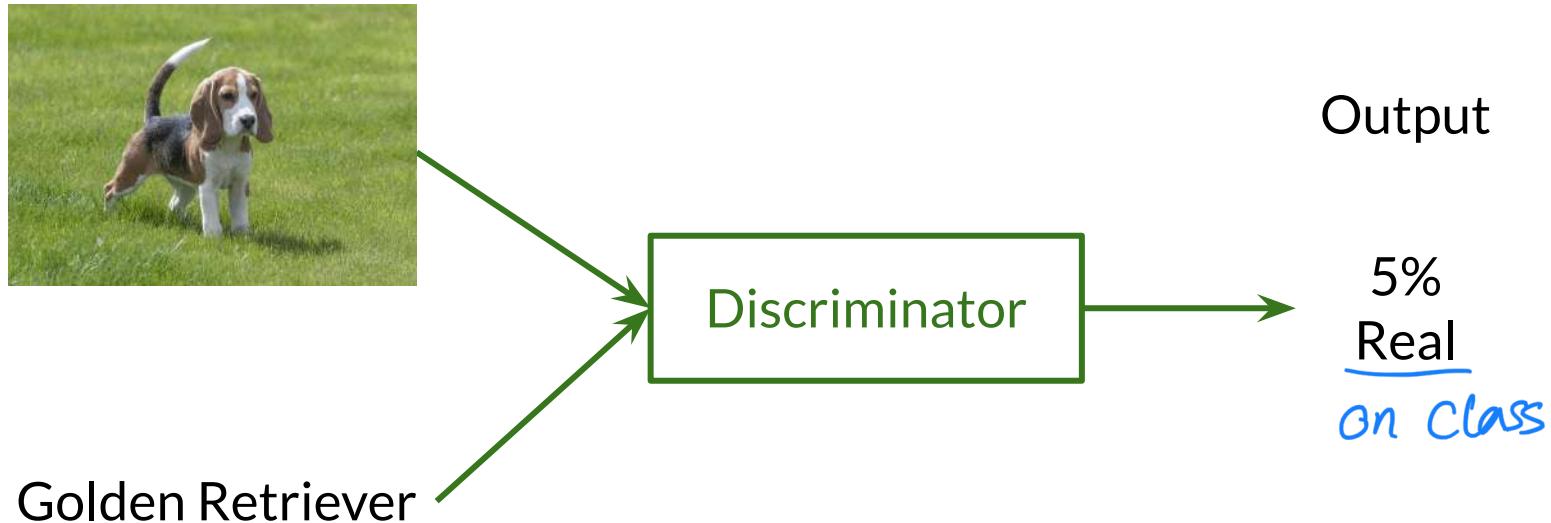
# Discriminator Input

Discriminator

# Discriminator Input



# Discriminator Input



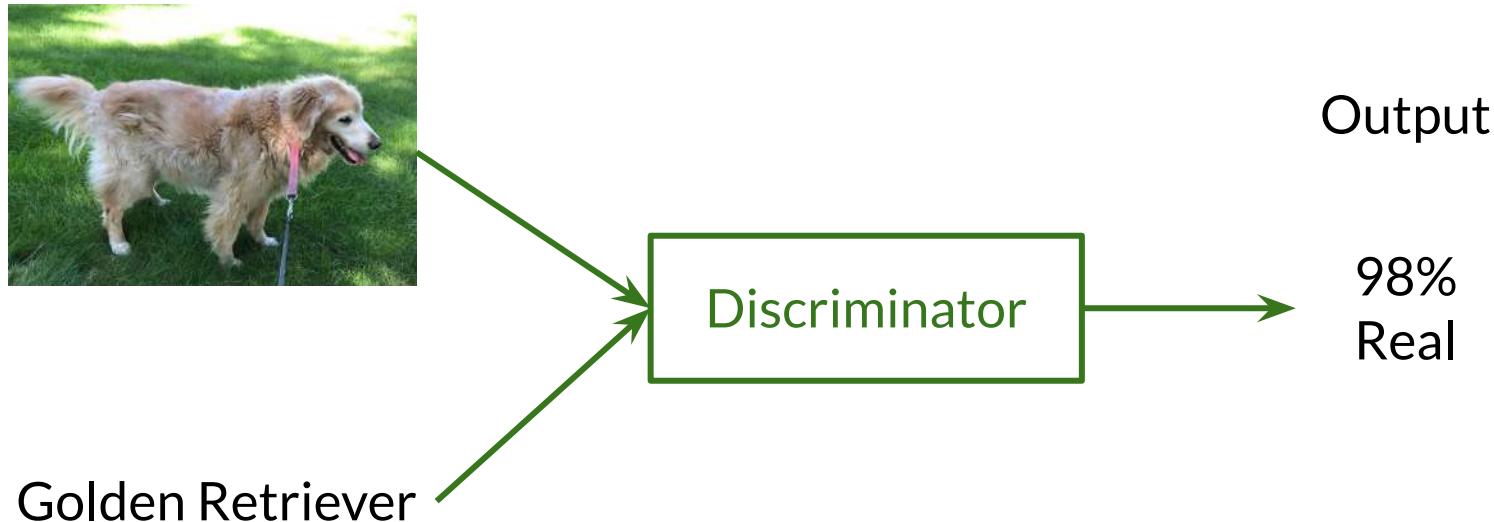
# Discriminator Input



Discriminator

Golden Retriever

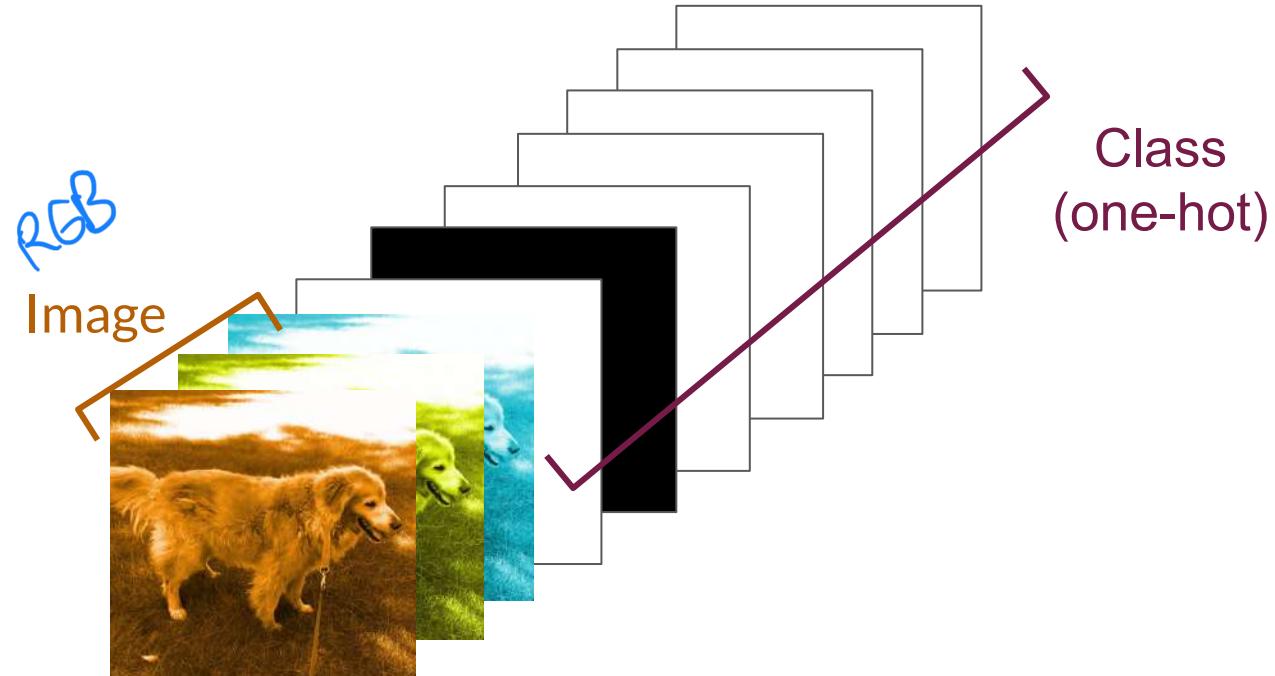
# Discriminator Input



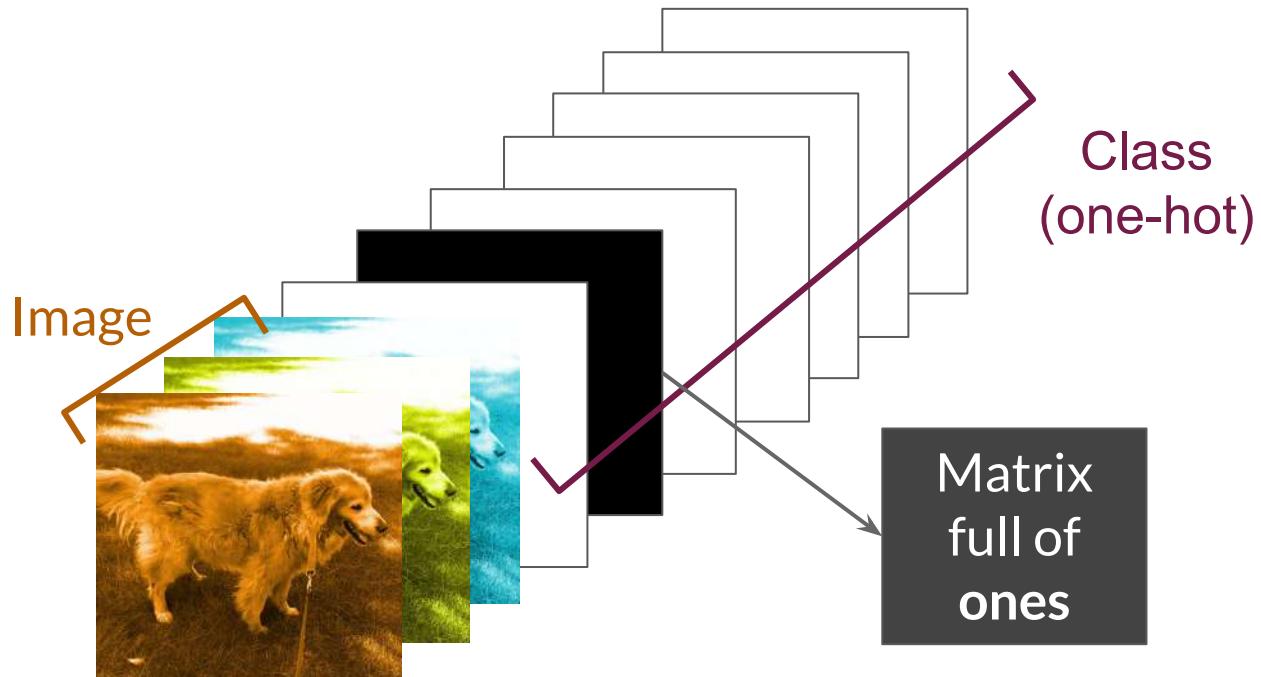
# Discriminator Input



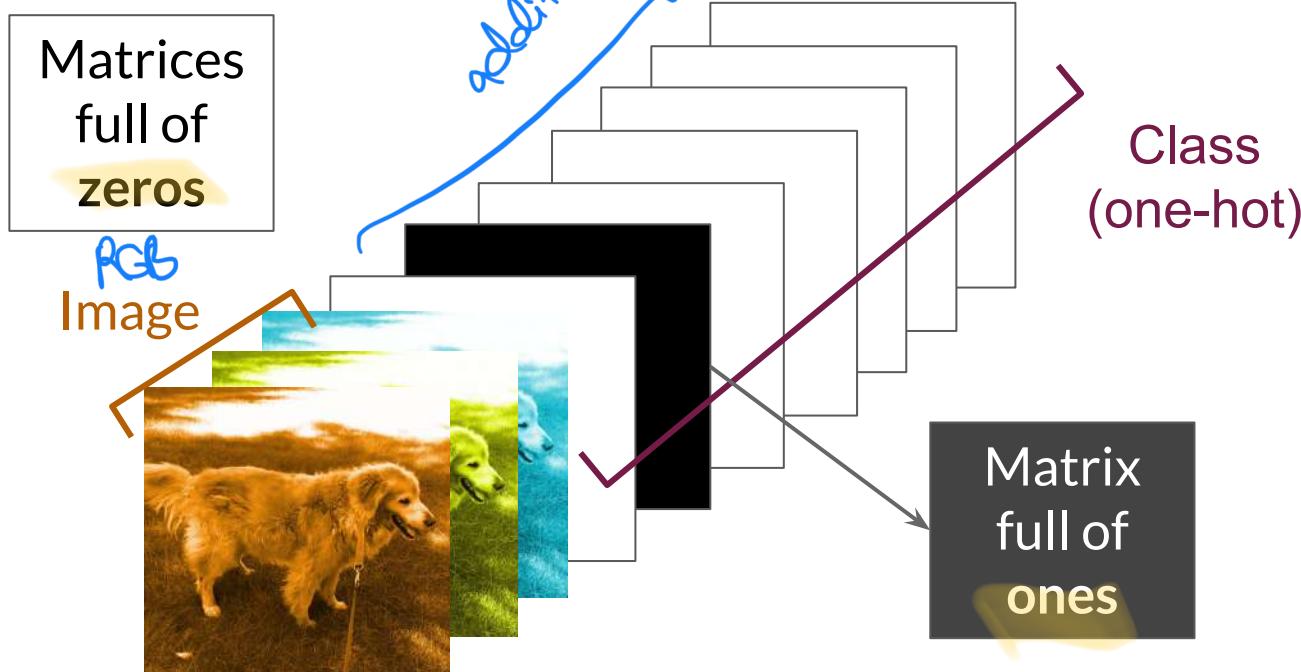
# Discriminator Input



# Discriminator Input



# Discriminator Input



# Summary

- The class is passed to the generator as one-hot vectors
- The class is passed to the discriminator as one-hot matrices
- The size of the vector and the number of matrices represent the number of classes



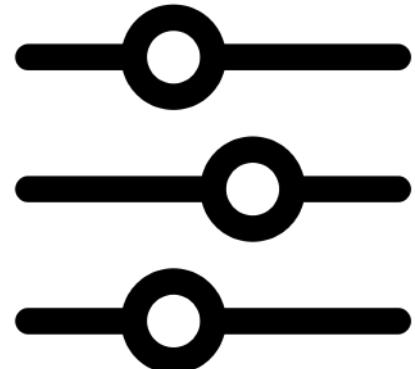


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# Controllable Generation

# Outline

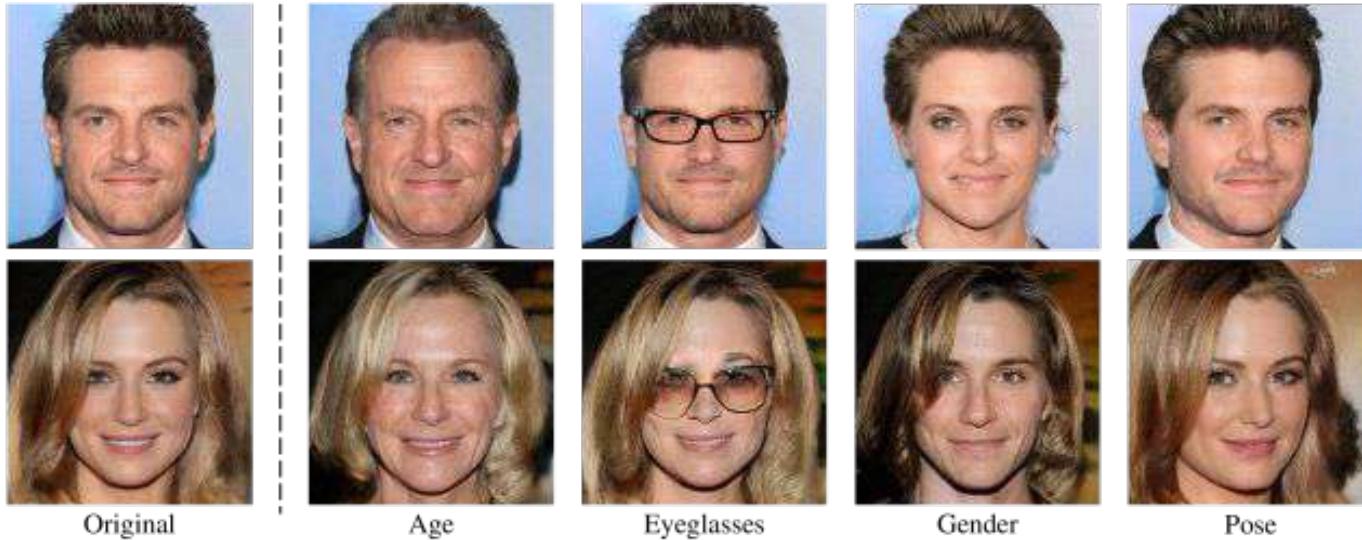
- What is controllable generation
- How it compares to conditional generation



# Controllable Generation

Change specific features of the output

# Controllable Generation



Change specific features of the output

Available from: <https://arxiv.org/abs/1907.10786>

# Controllable Generation

Noise vector

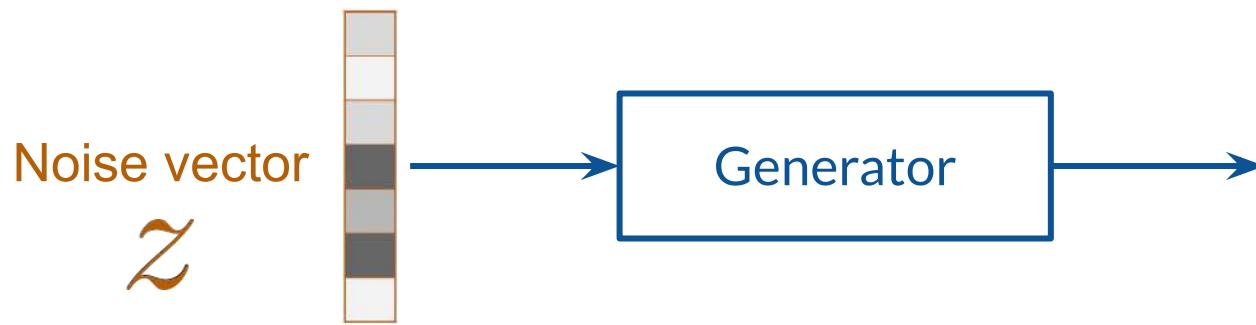
$\tilde{z}$



Tweak the input noise vector to get different features on the output

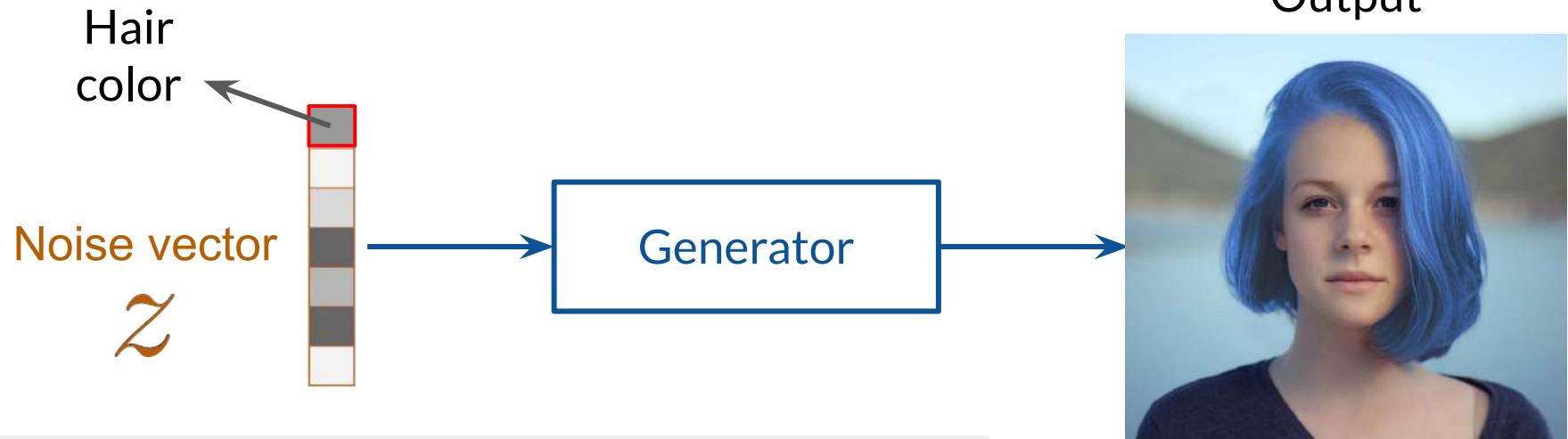
# Controllable Generation

Controlled  
Output



Tweak the input noise vector to get different features on the output

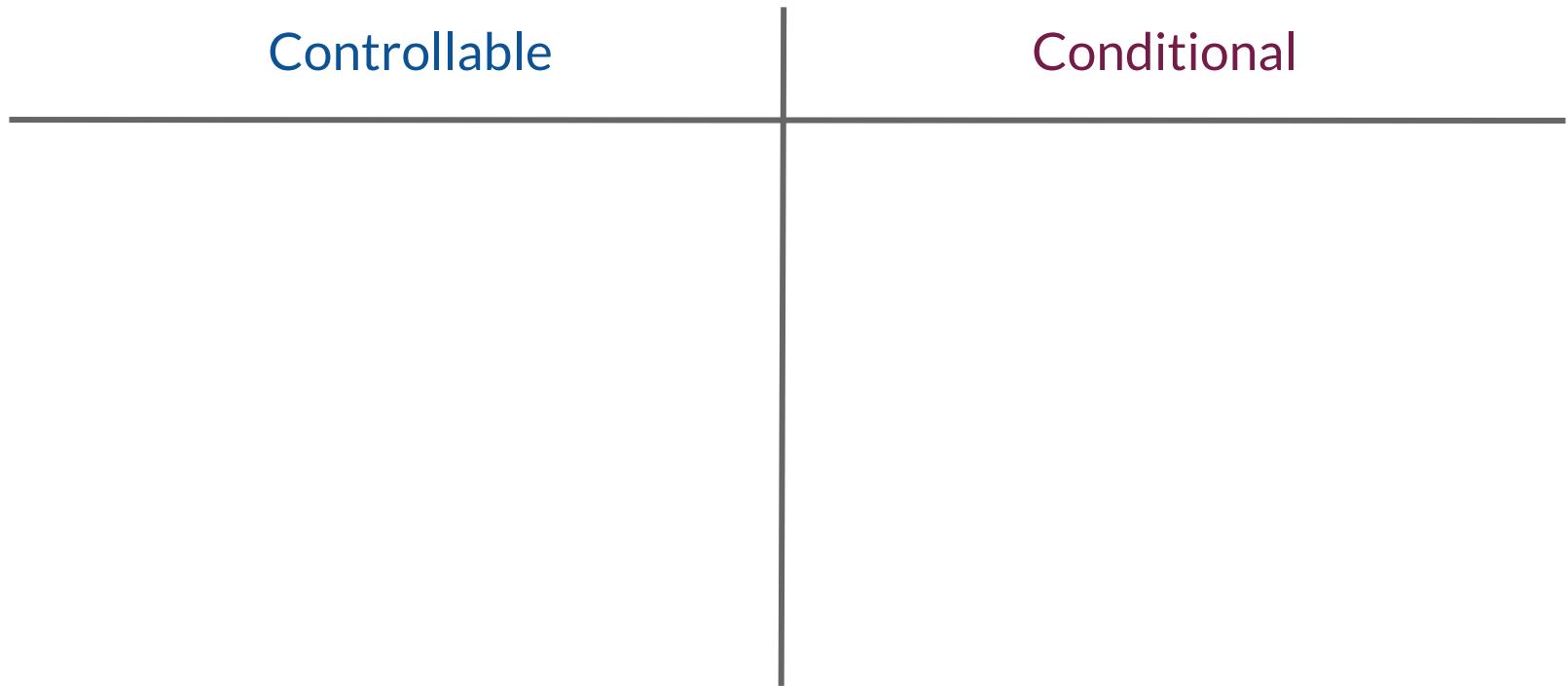
# Controllable Generation



Tweak the input noise vector to get different features on the output

Controlled Output

# Controllable Generation vs. Conditional Generation



# Controllable Generation vs. Conditional Generation

Controllable	Conditional
Examples with the <b>features that you want</b>	Examples from <i>the classes you want</i>

# Controllable Generation vs. Conditional Generation

Controllable	Conditional
Examples with the <b>features that you want</b>	Examples from <i>the classes you want</i>
Training dataset <b>doesn't need to be labeled</b>	Training dataset <i>needs to be labeled</i>

# Controllable Generation vs. Conditional Generation

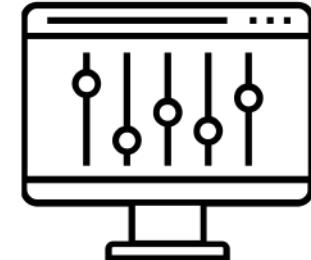
Controllable	Conditional
Examples with the features that you want	Examples from <i>the classes you want</i>
Training dataset <b>doesn't need to be labeled</b>	Training dataset <b>needs to be labeled</b>
 Manipulate the z vector input	 Append a class vector to the input

it is done after training  
By changing the z vector.



# Summary

- Controllable generation lets you control the features of the generated outputs
- It does not need a labeled training dataset
- The input vector is tweaked to get different features on the output



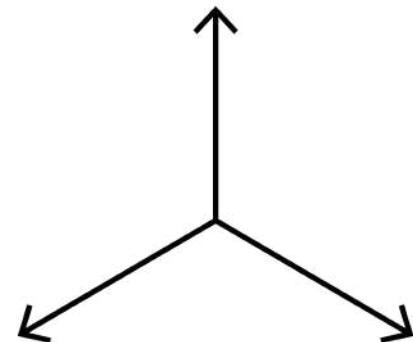


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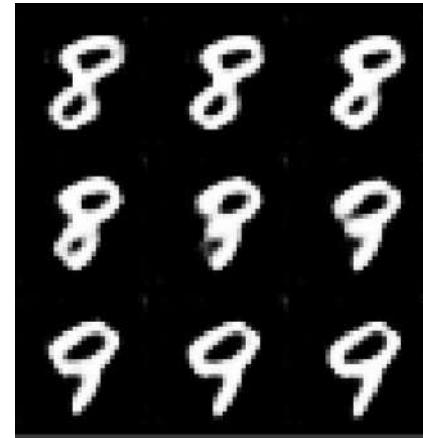
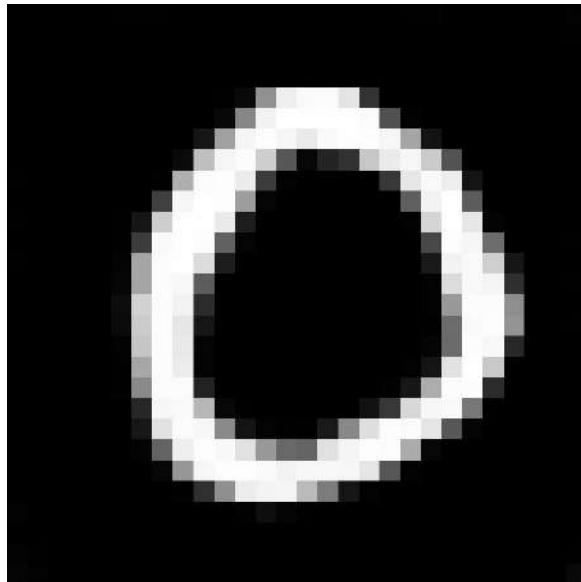
# Vector Algebra in the Z-Space

# Outline

- Interpolation in the Z-space
- Modifying the noise vector  $z$  to control desired features

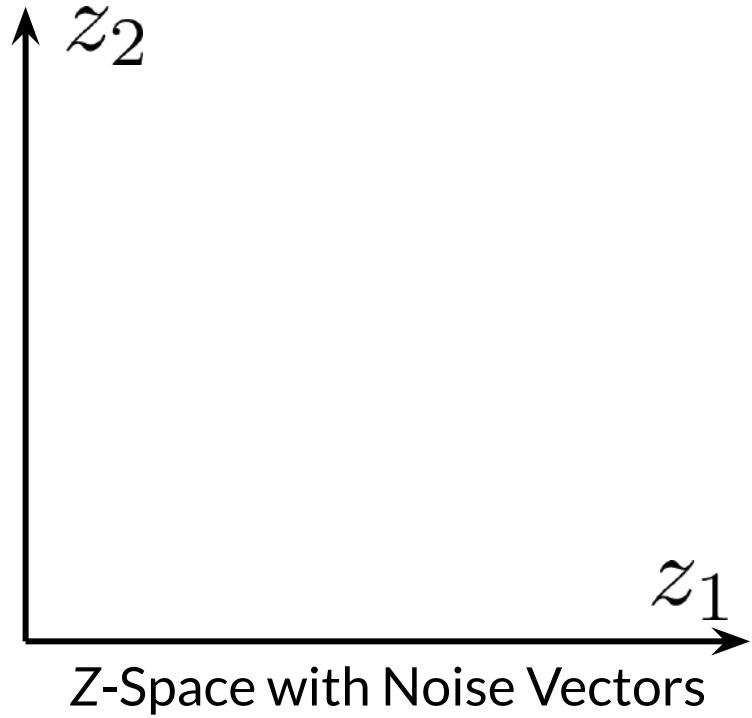


# Interpolation Using the Z-Space

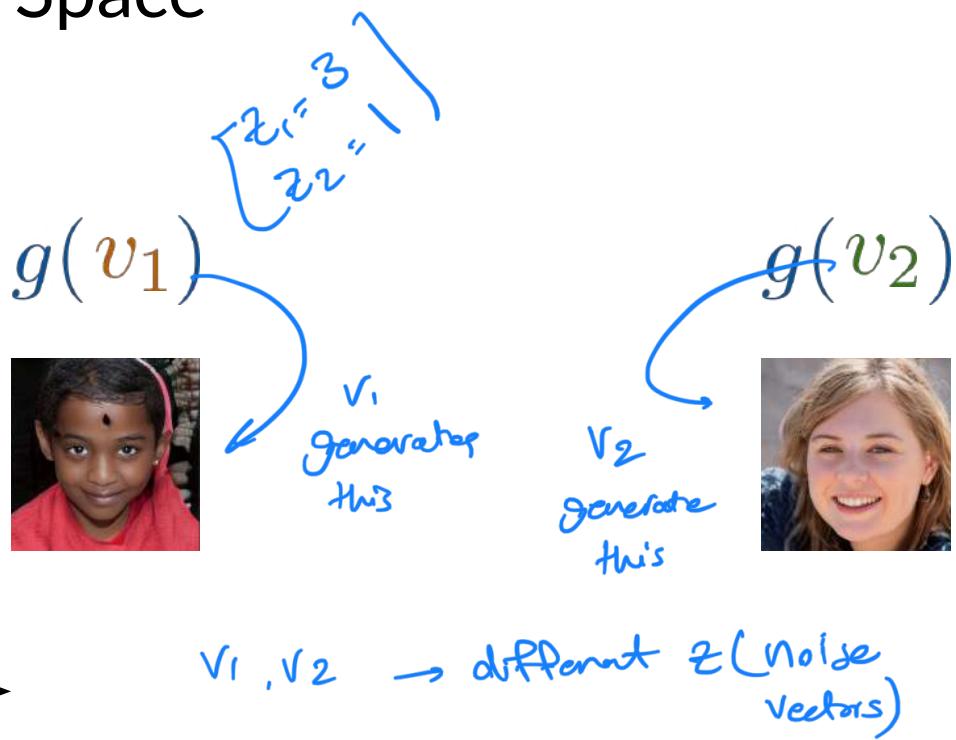
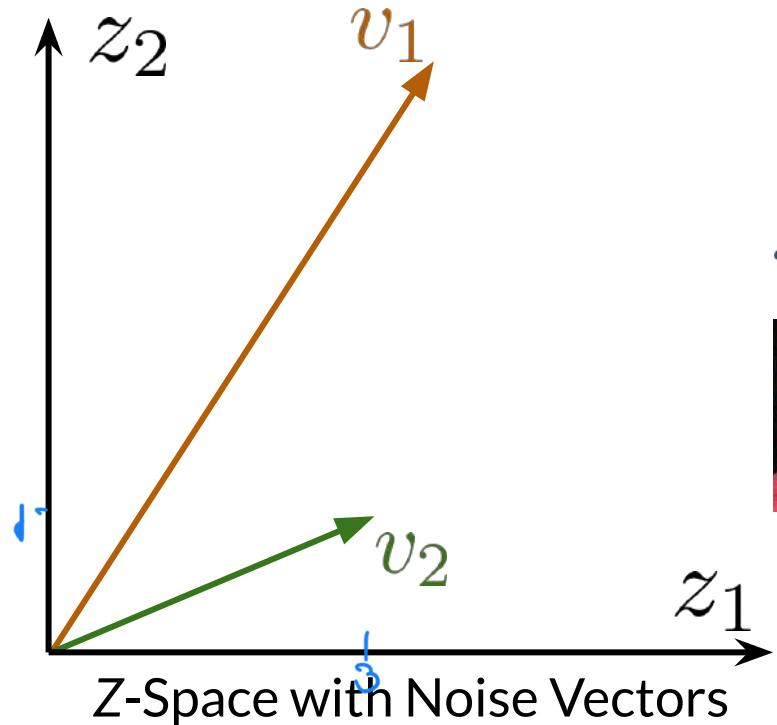


How an image morphs into another

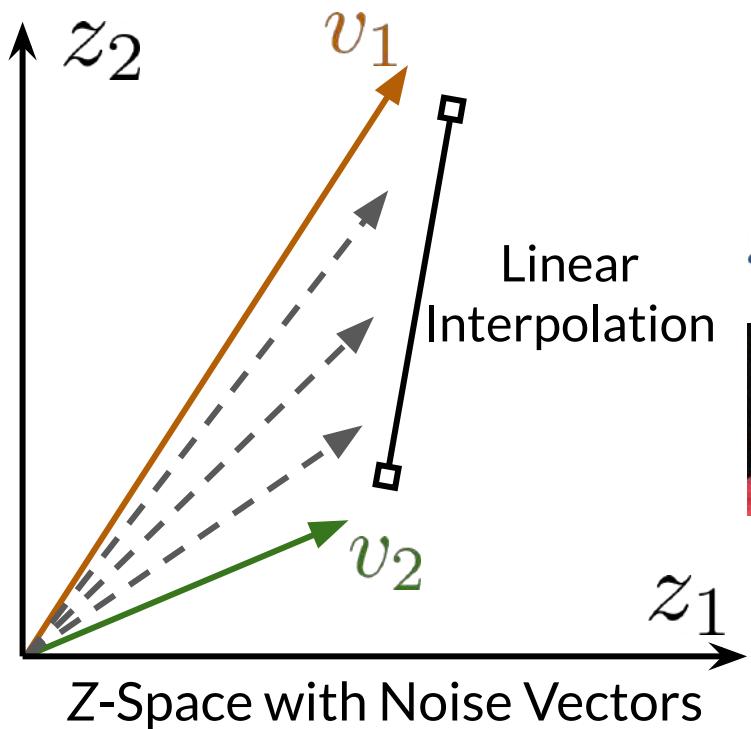
# Interpolation Using the Z-Space



# Interpolation Using the Z-Space



# Interpolation Using the Z-Space



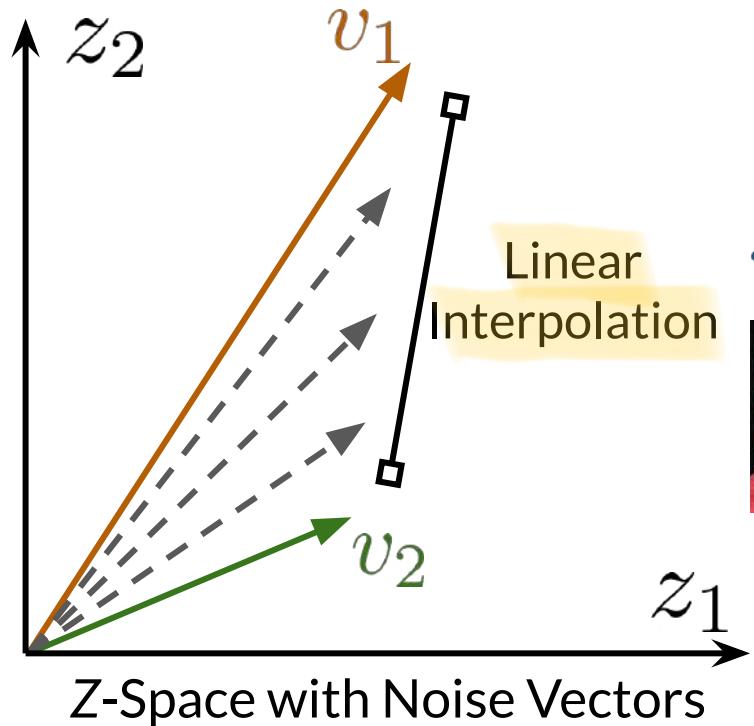
$g(v_1)$



$g(v_2)$



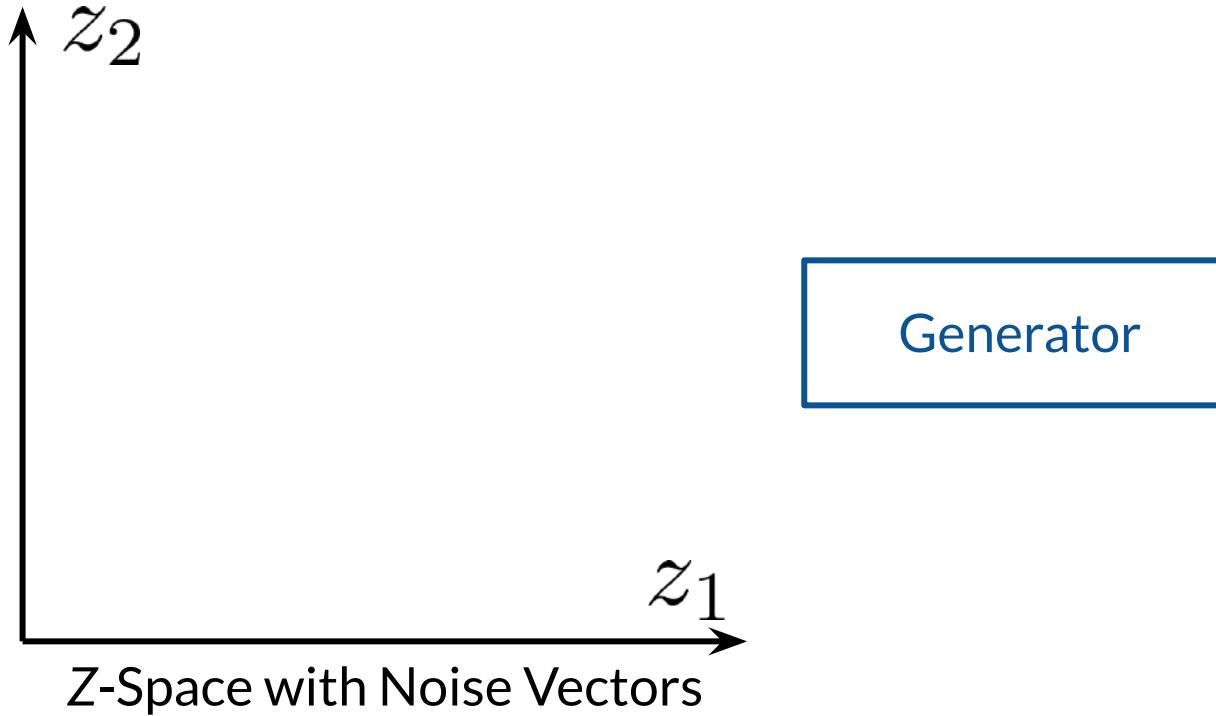
# Interpolation Using the Z-Space



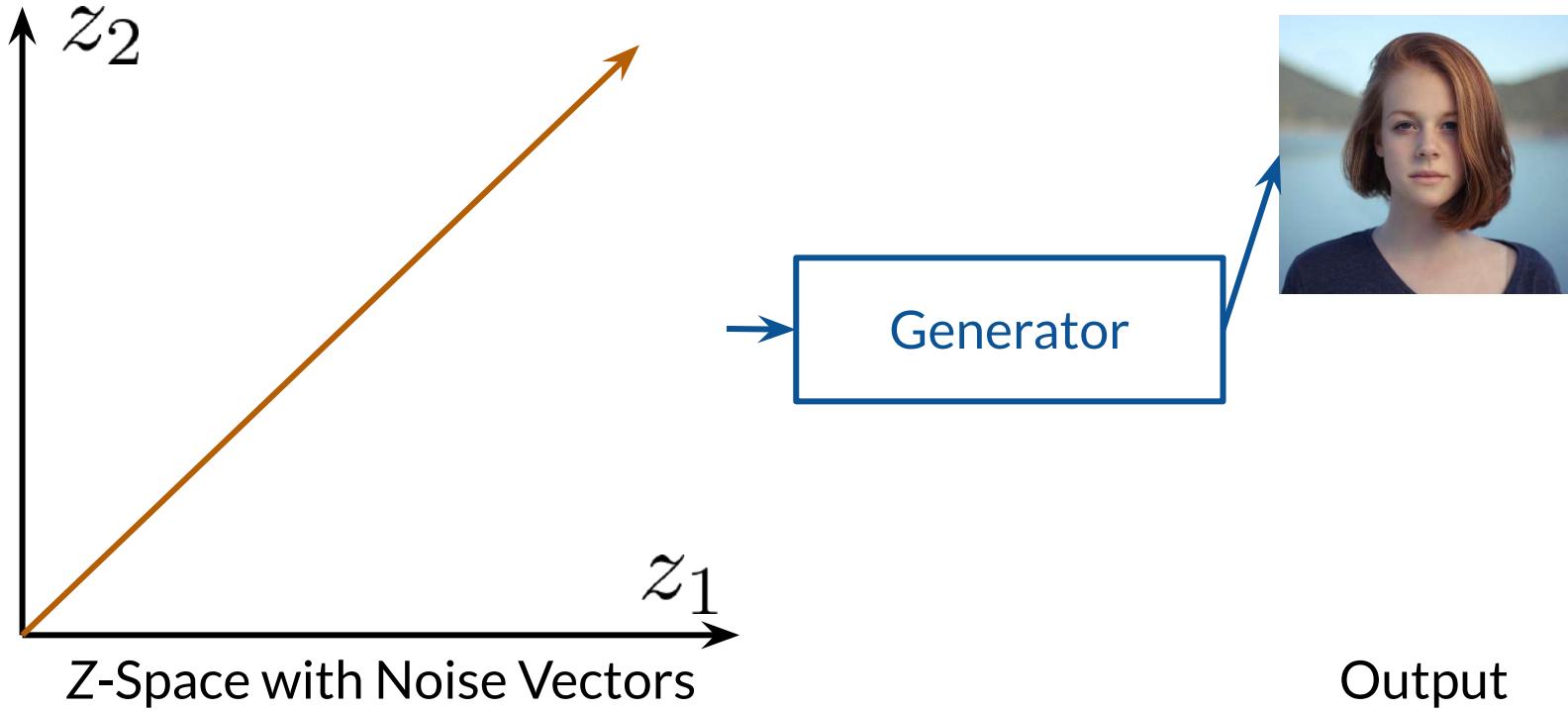
Intermediate images using  
 $g(v_1)$  ← →  $g(v_2)$



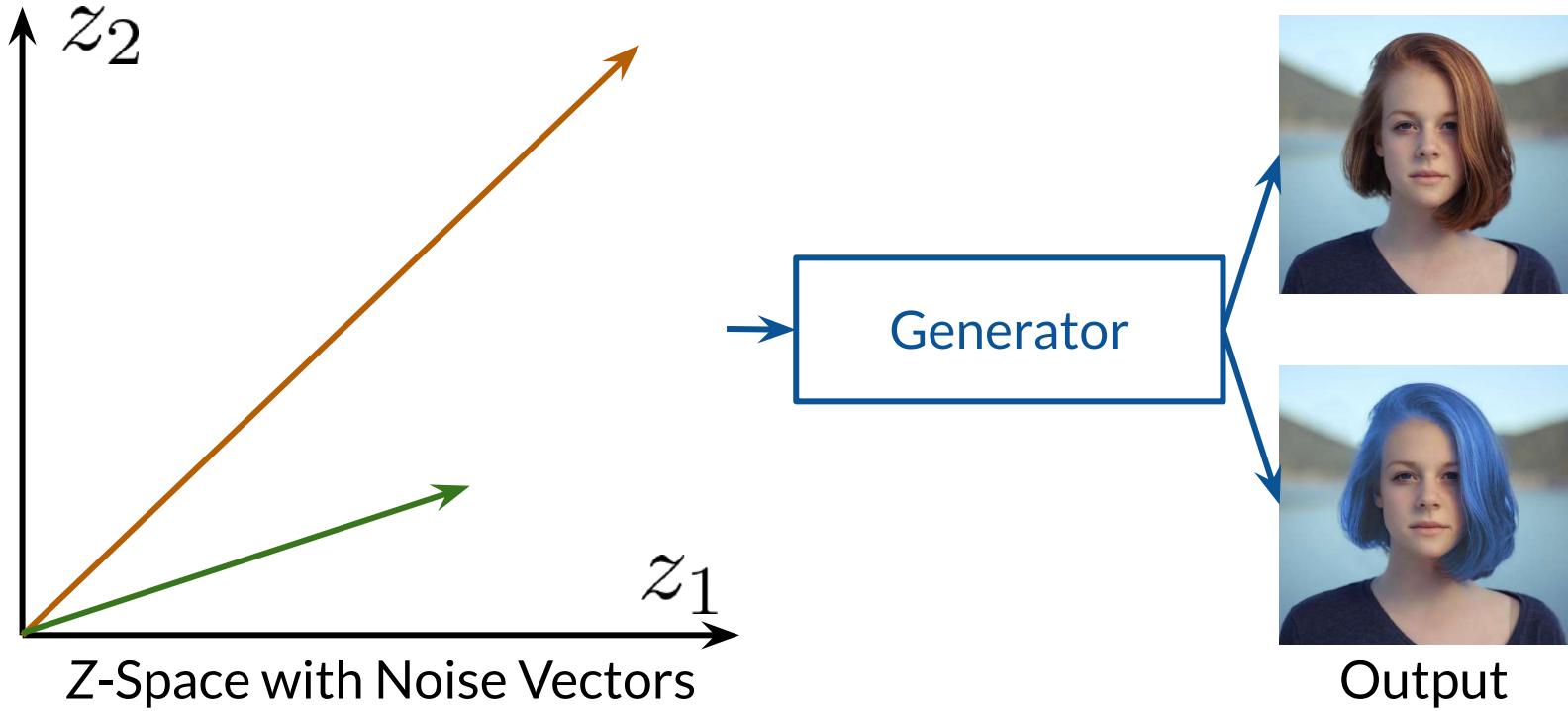
# Z-Space and Controllable Generation



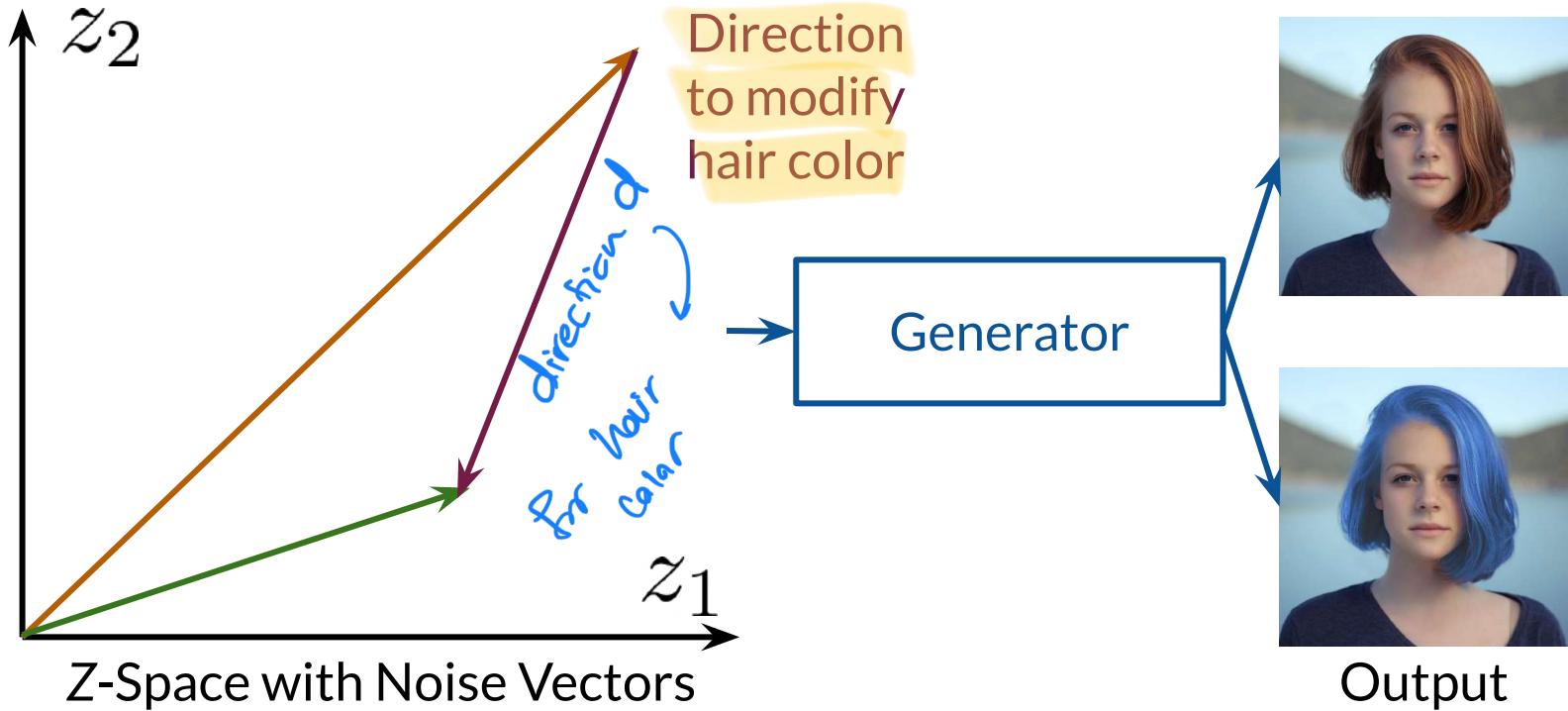
# Z-Space and Controllable Generation



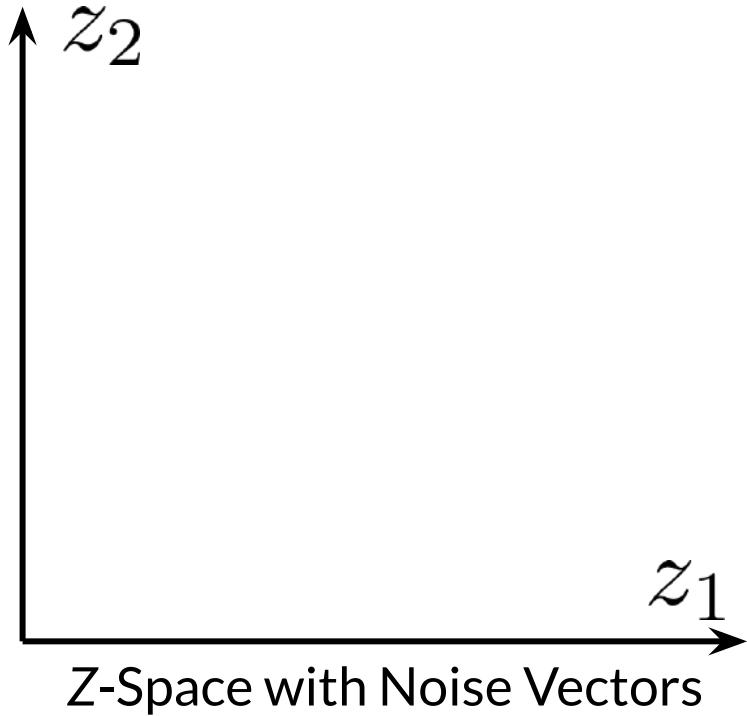
# Z-Space and Controllable Generation



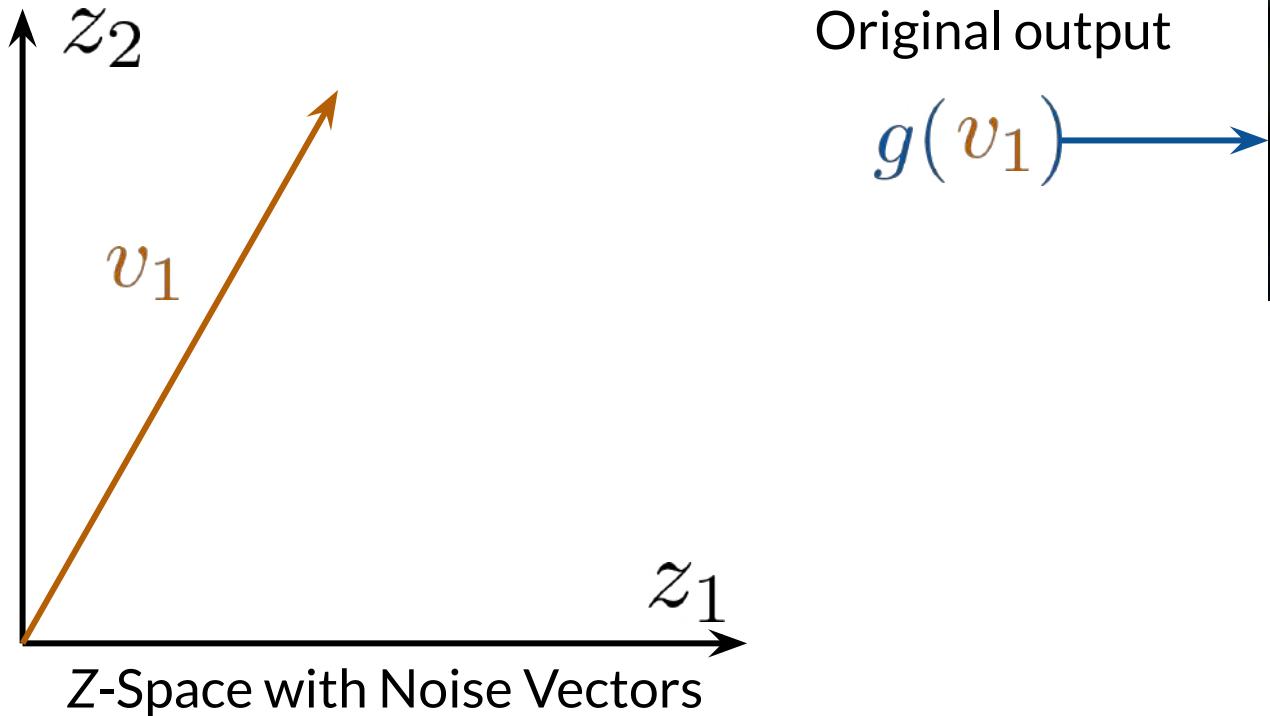
# Z-Space and Controllable Generation



# Z-Space and Controllable Generation



# Z-Space and Controllable Generation

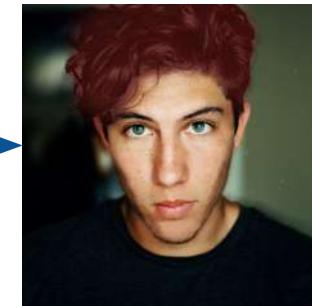
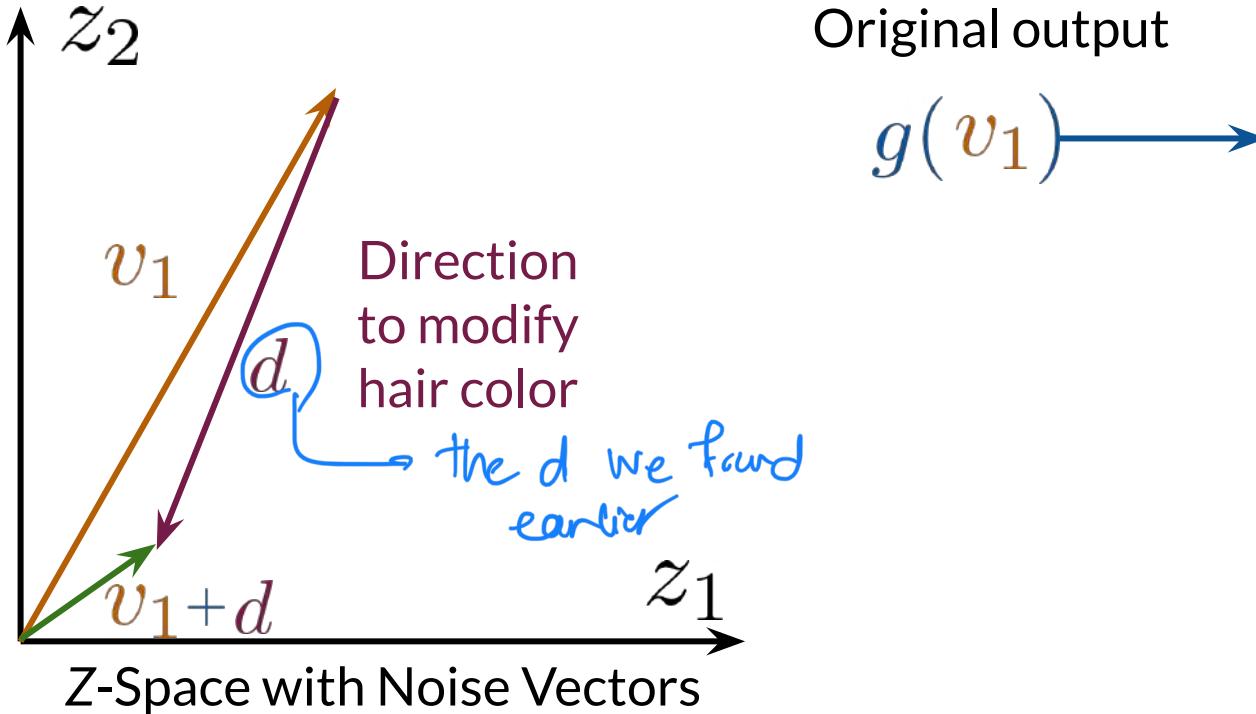


Original output

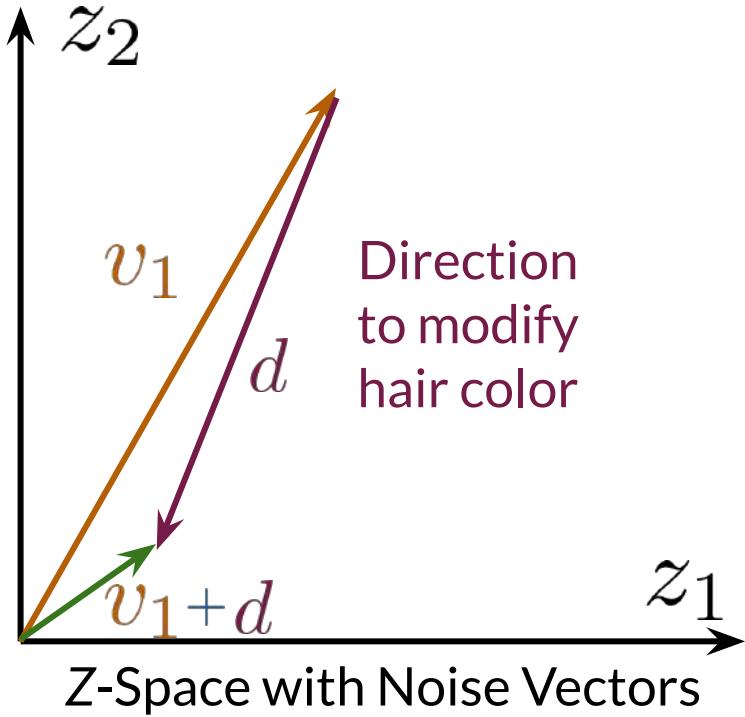
$$g(v_1) \longrightarrow$$



# Z-Space and Controllable Generation



# Z-Space and Controllable Generation



Original output

$$g(v_1) \rightarrow$$



Controlled output

$$g(v_1 + d) \rightarrow$$

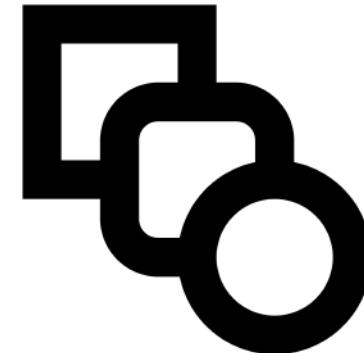


# Summary

- To control output features, you need to find directions in the Z-space
- To modify your output, you move around in the Z-space

Controllable GAN

↳ Find directions in Z space  
that gives us the desired  
Features.





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# Challenges with Controllable Generation

# Outline

- Output feature correlation
- Z-space entanglement



# Feature Correlation

Uncorrelated  
Features



Add beard



# Feature Correlation

Uncorrelated  
Features



Woman & Beard  
are uncorrelated!

Add beard

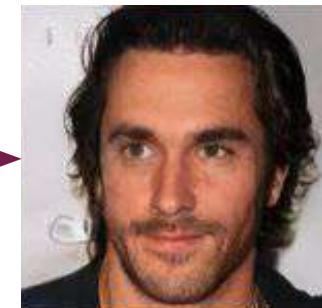


Correlated  
Features



Add beard

Make more  
masculine



↳ modifying more features

But we want directions that only change one feature

# Z-Space Entanglement

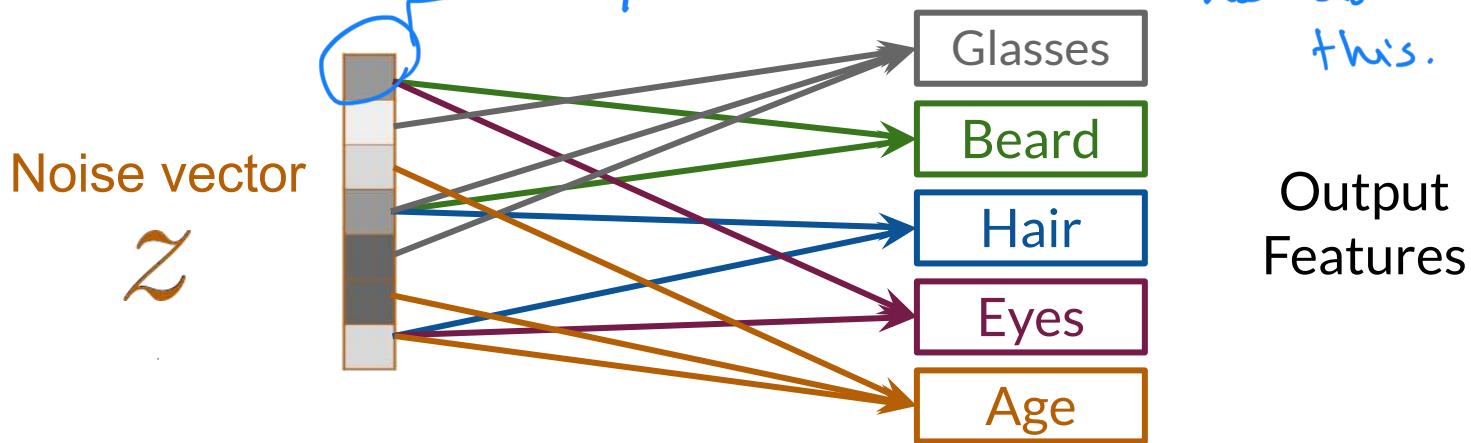
Noise vector

$\tilde{z}$

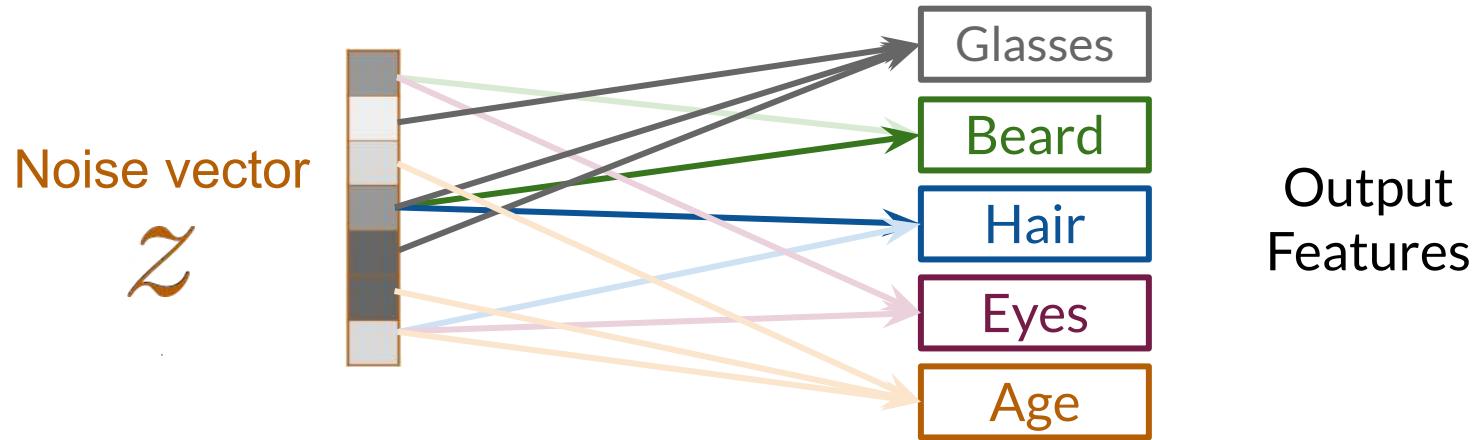


Output  
Features

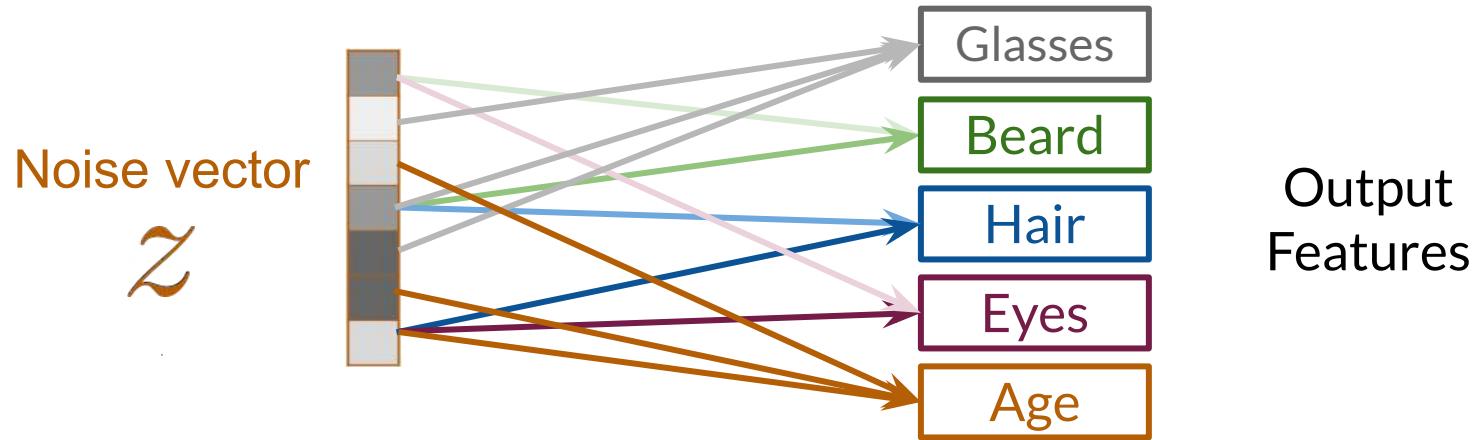
# Z-Space Entanglement



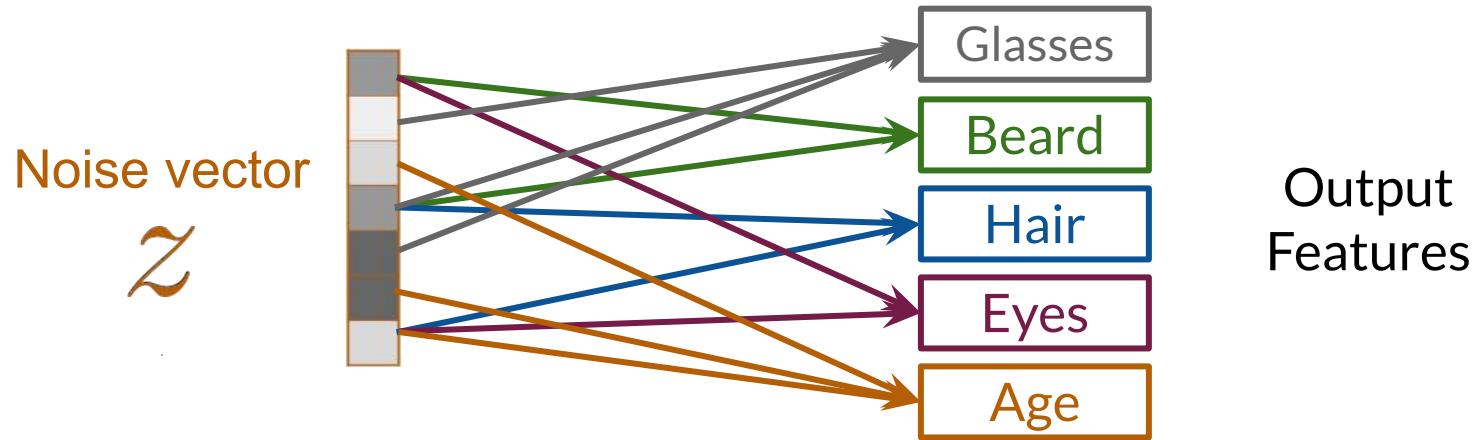
# Z-Space Entanglement



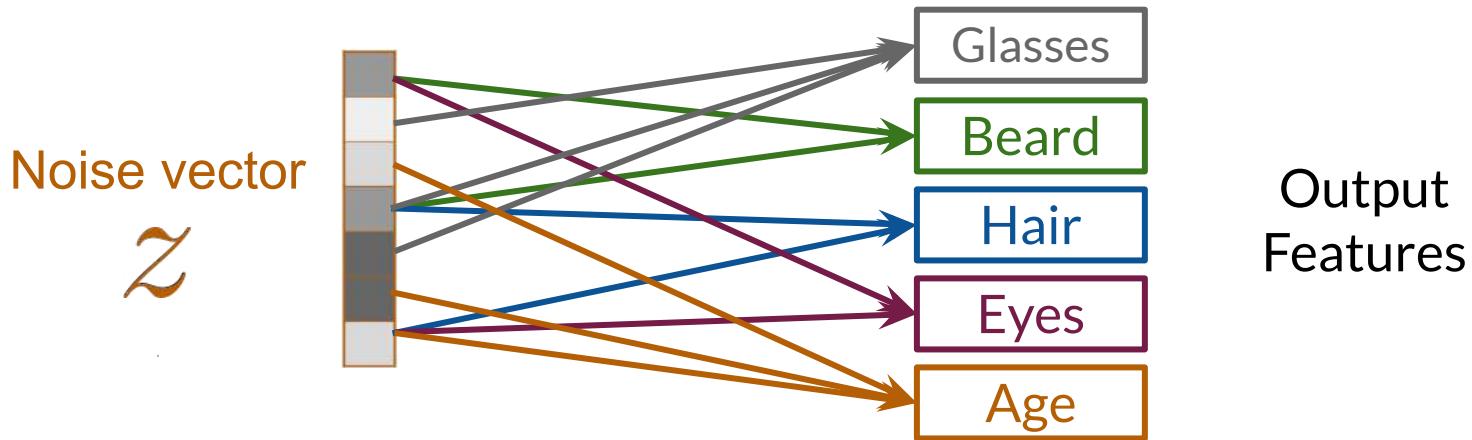
# Z-Space Entanglement



# Z-Space Entanglement

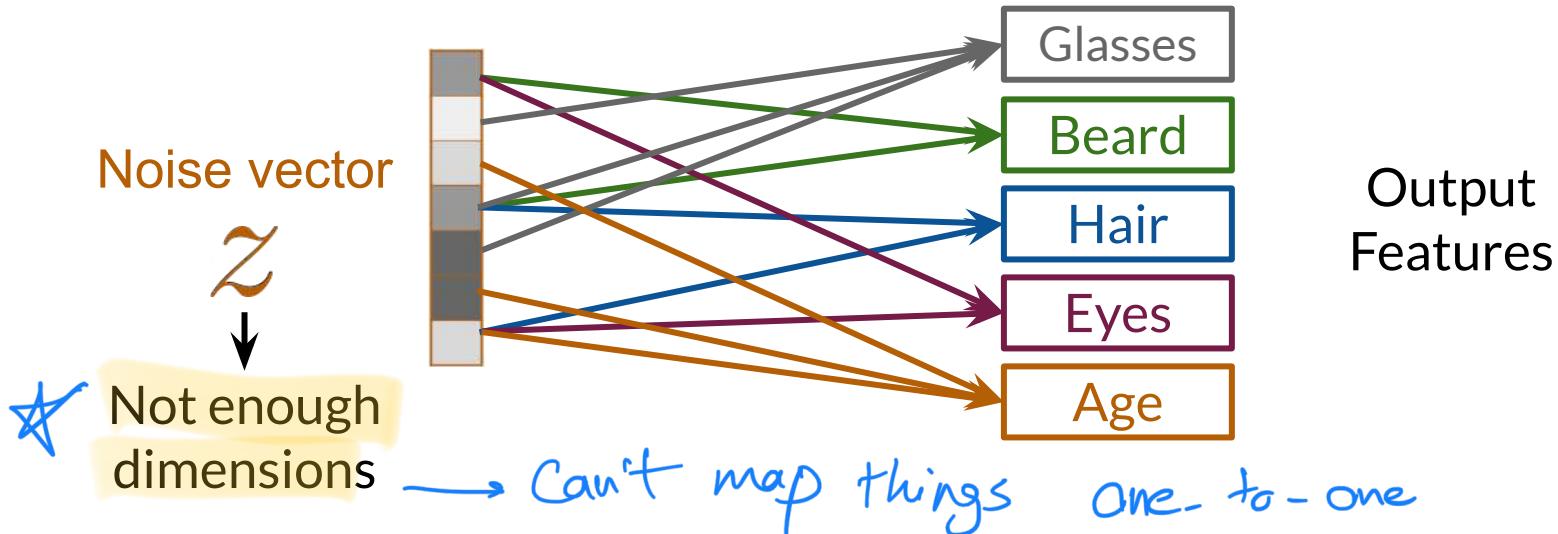


# Z-Space Entanglement



It is not possible to control single output features

# Z-Space Entanglement



It is not possible to control single output features

# Summary

- When trying to control one feature, others that are correlated change
- Z-space entanglement makes controllability difficult, if not impossible
- Entanglement happens when z does not have enough dimensions





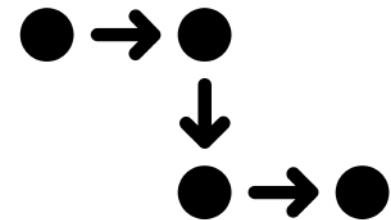
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# Classifier Gradients

# Outline

- How to use classifiers to find directions in the Z-space
- Requirements to use this method

How to find that direction of  
we wanted!



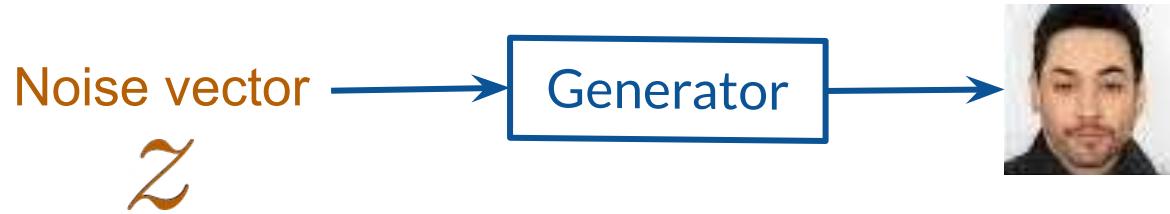
# Classifier Gradients

# Classifier Gradients

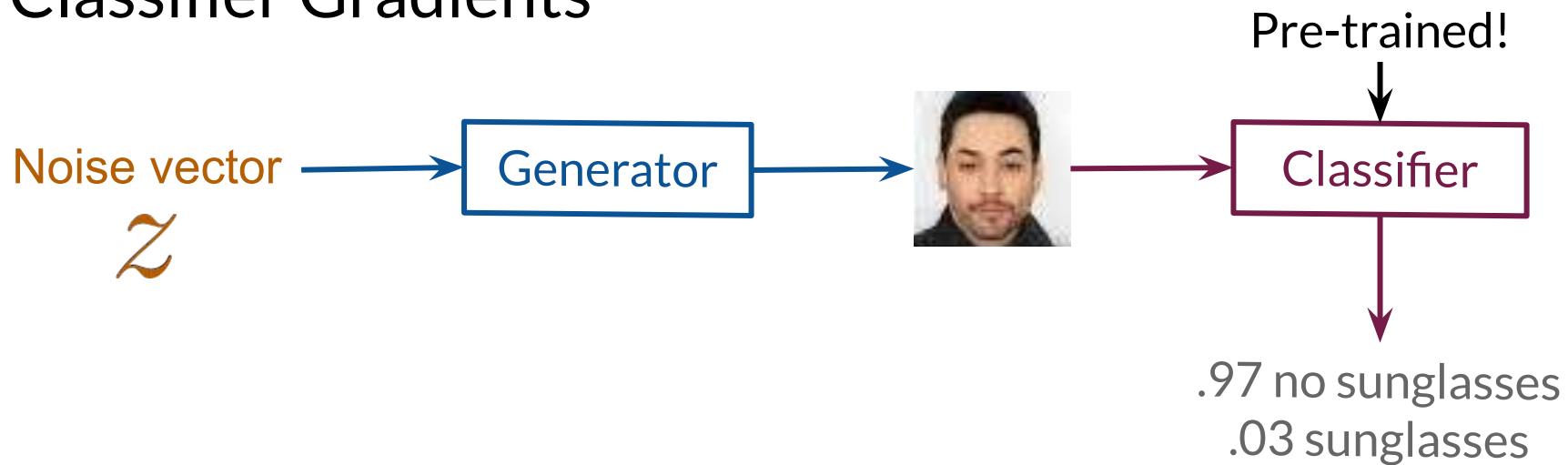
Noise vector

$\tilde{z}$

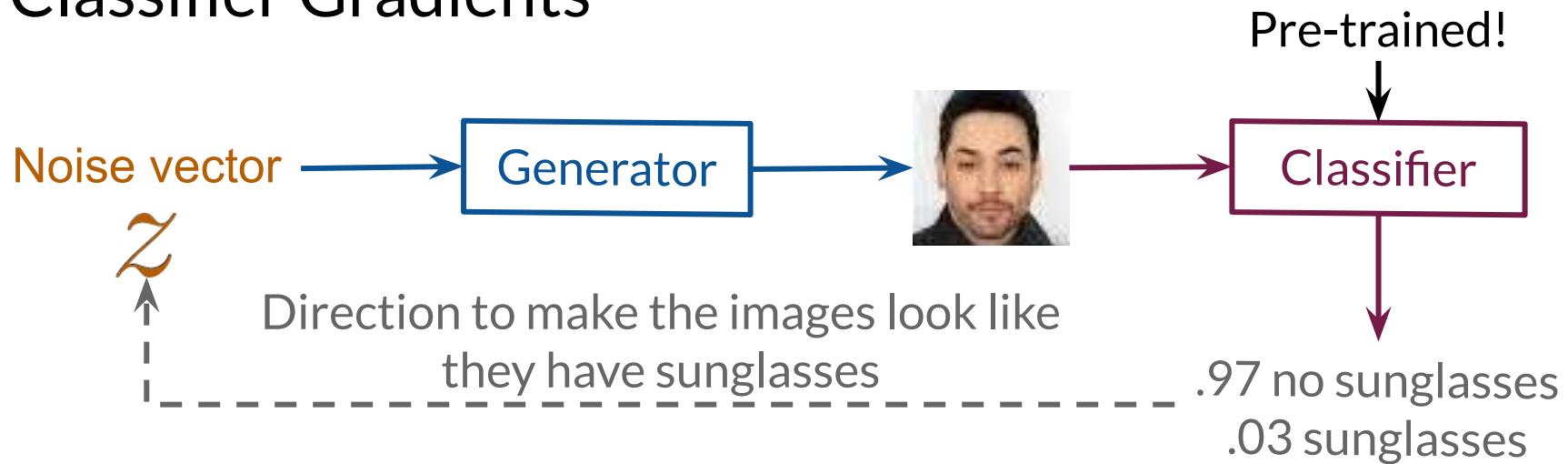
# Classifier Gradients



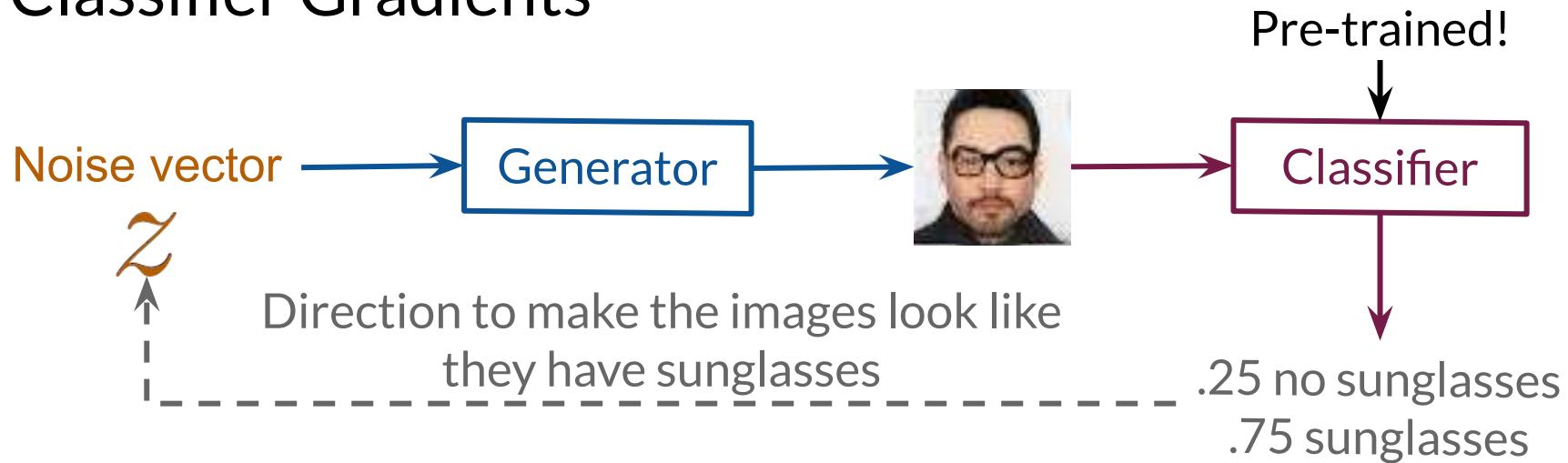
# Classifier Gradients



# Classifier Gradients



# Classifier Gradients

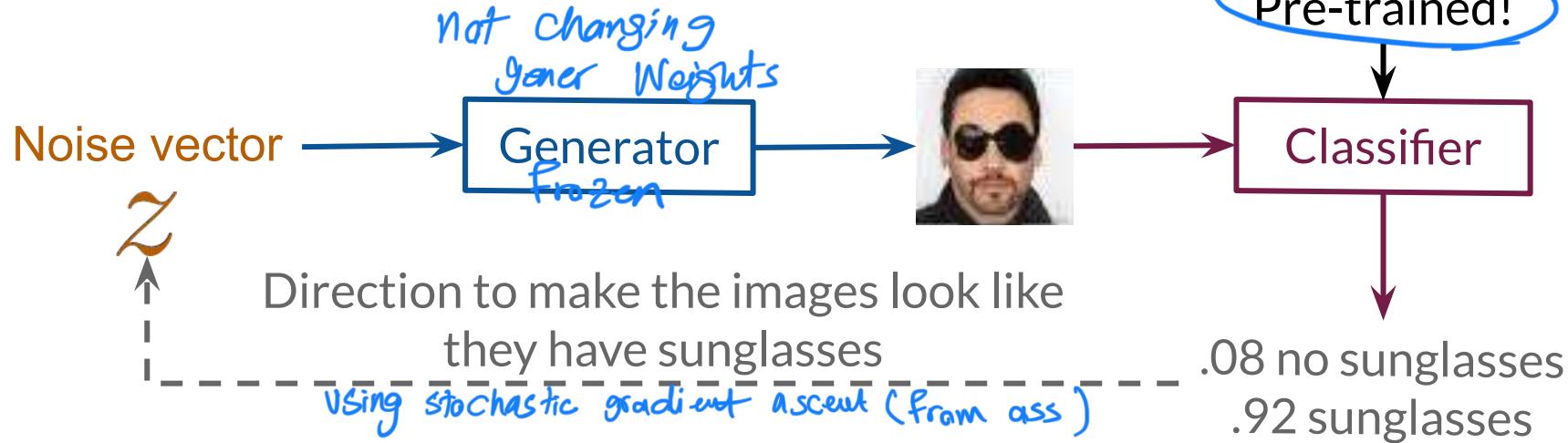


Modify just the **noise vector** until the feature emerges

all of this happen after GAN training.

Sunglass classifier

## Classifier Gradients



Modify just the **noise vector** until the feature emerges

Can's

↳ We need a classifier that is trained on the feature we want.

# Summary

- Classifiers can be used to find directions in the Z-space
- To find directions, the updates are done just to the noise vector





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# Disentanglement

# Outline

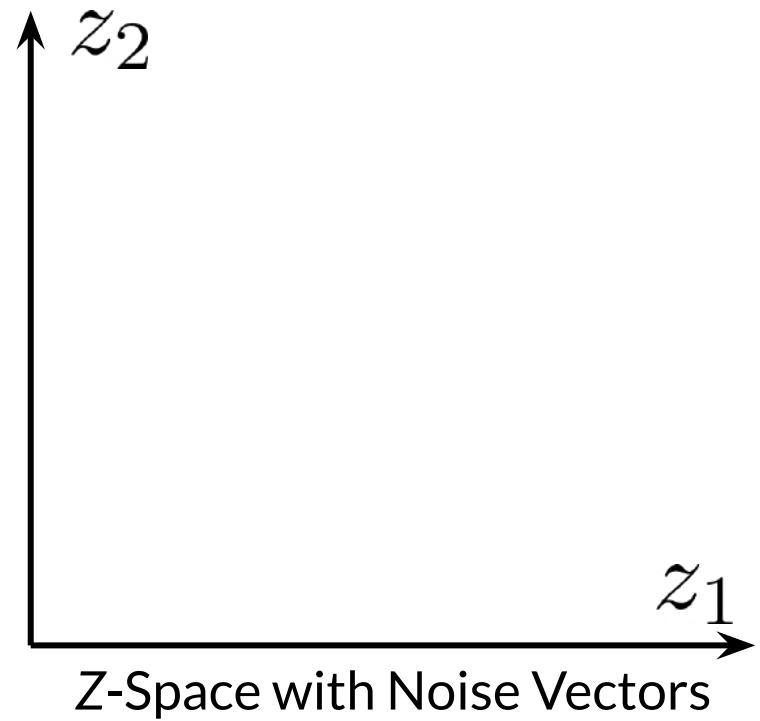
- What a disentangled Z-space means
- Ways to encourage disentangled Z-spaces



# Disentangled Z-Space

$$v_1 = [1, 2, 3, \dots]$$

$$v_2 = [5, 6, 7, \dots]$$

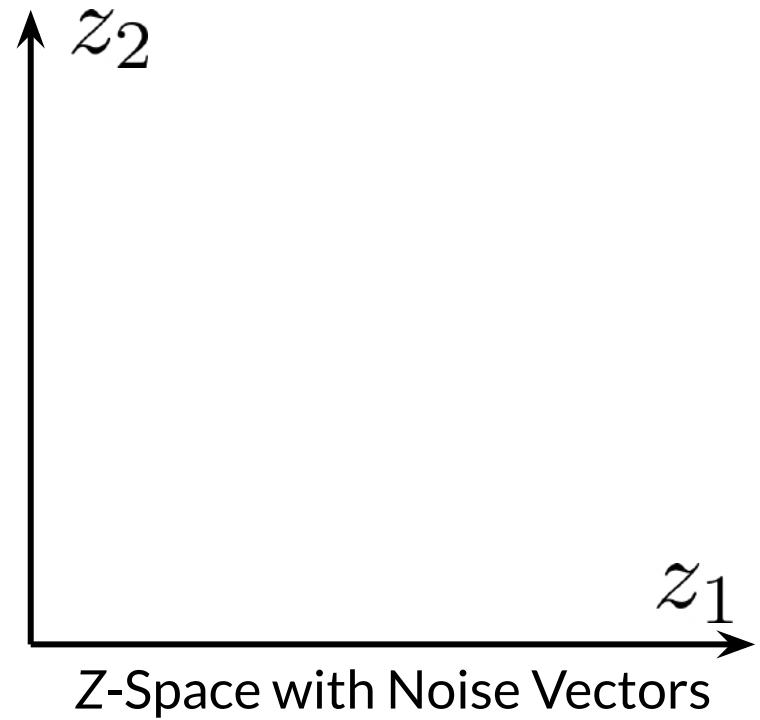


# Disentangled Z-Space

$$v_1 = [ \underset{\text{Hair color}}{\textcolor{brown}{1}}, 2, 3, \dots ]$$

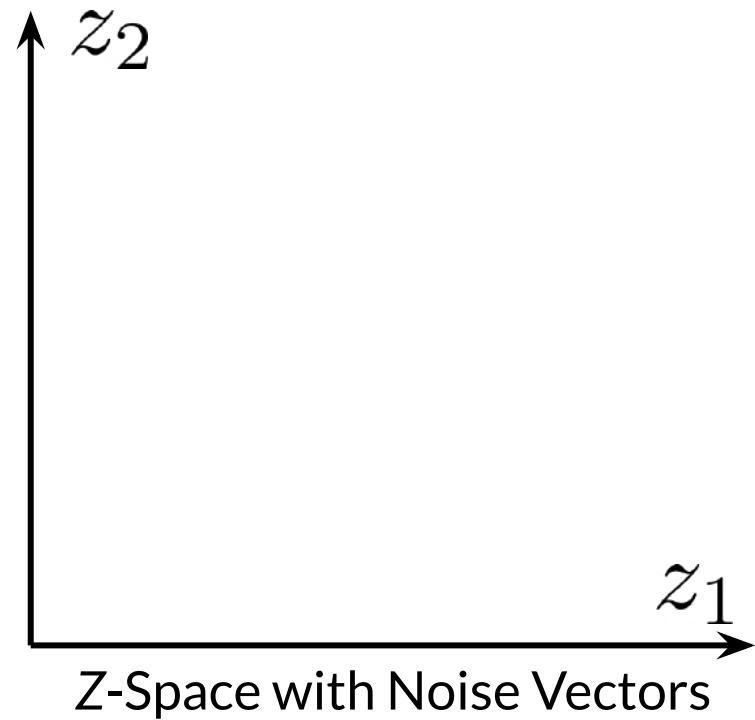
$$v_2 = [ \underset{\text{Hair color}}{\textcolor{brown}{5}}, 6, 7, \dots ]$$

Hair  
color



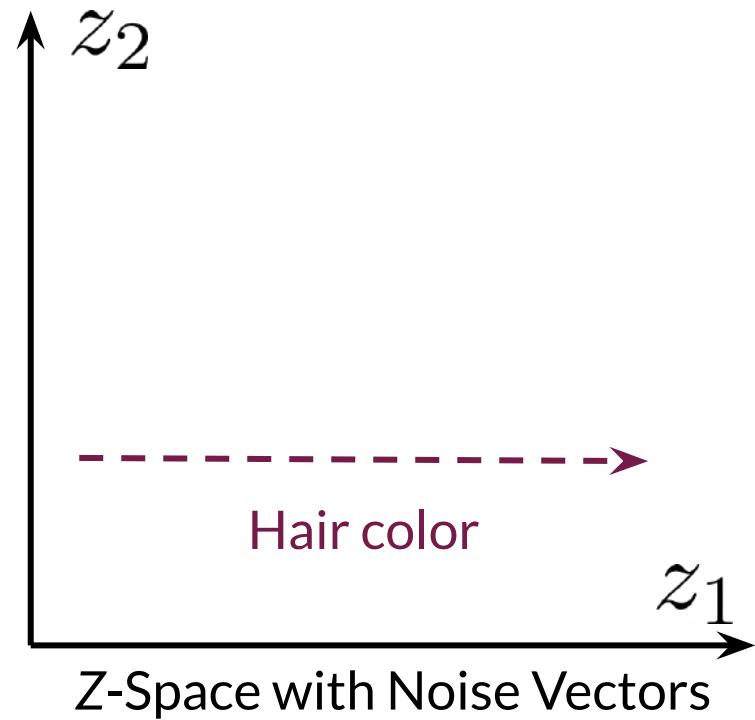
# Disentangled Z-Space

$$\begin{array}{c} z_1 \quad z_2 \\ v_1 = [ \textcolor{red}{1}, \textcolor{blue}{2}, 3, \dots ] \\ v_2 = [ \textcolor{red}{5}, \textcolor{blue}{6}, 7, \dots ] \\ \text{Hair color} \qquad \qquad \text{Hair length} \end{array}$$



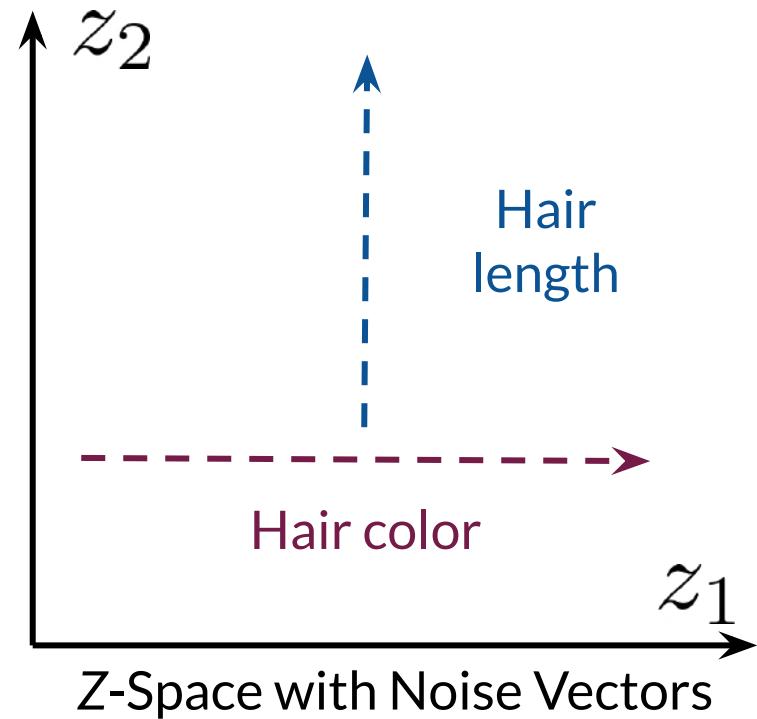
# Disentangled Z-Space

$$v_1 = [ \underset{\text{Hair color}}{\textcolor{red}{1}}, \underset{\text{Hair length}}{\textcolor{blue}{2}}, 3, \dots ]$$
$$v_2 = [ \underset{\text{Hair color}}{\textcolor{red}{5}}, \underset{\text{Hair length}}{\textcolor{blue}{6}}, 7, \dots ]$$



# Disentangled Z-Space

$$\begin{matrix} & z_1 & z_2 \\ v_1 = & [ \textcolor{pink}{1}, & 2, & 3, \dots ] \\ v_2 = & [ \textcolor{pink}{5}, & 6, & 7, \dots ] \\ & \text{Hair color} & \text{Hair length} \end{matrix}$$



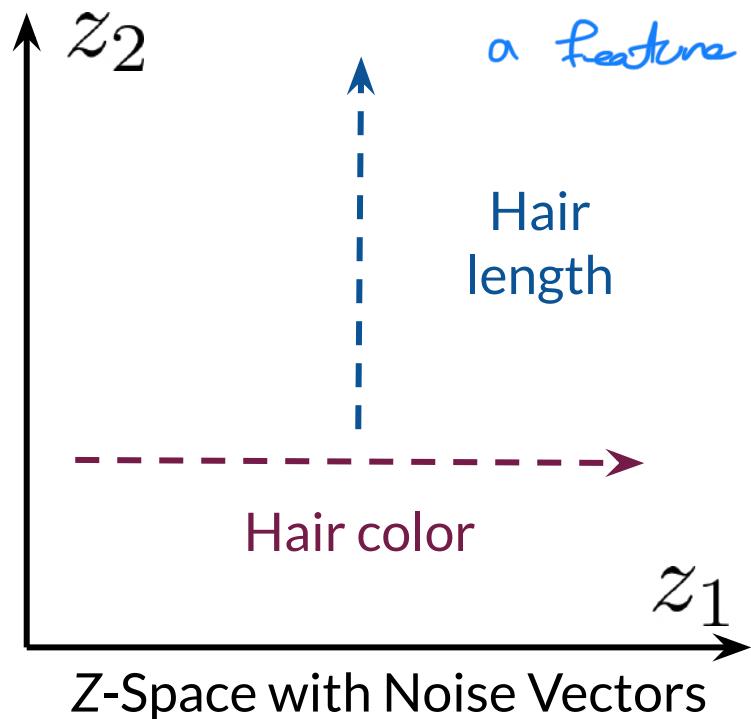
We want the size of  $v(\text{noise})$  vector to be larger than features we want. So after training each value could learn a feature

## Disentangled Z-Space

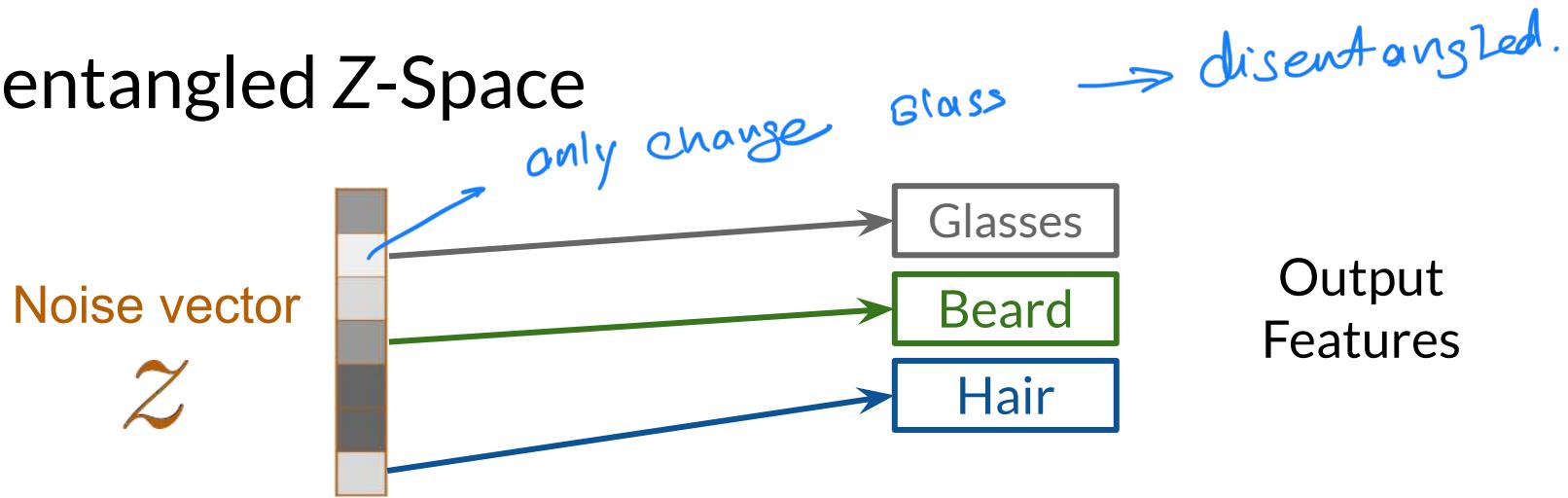
$$v_1 = [ \underset{\text{Hair color}}{1}, 2, 3, \dots ]$$

$$v_2 = [ \underset{\text{Hair length}}{5}, 6, 7, \dots ]$$

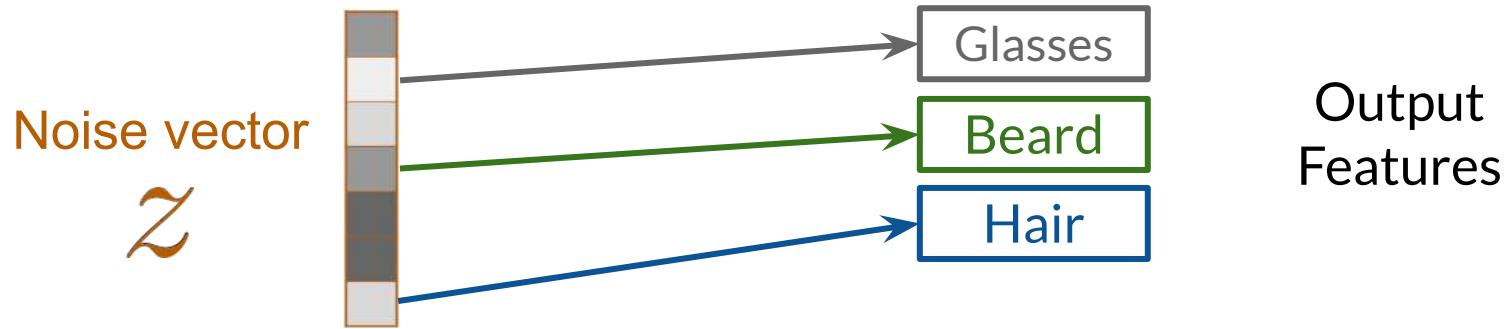
Latent factors of variation  
Feature



# Disentangled Z-Space

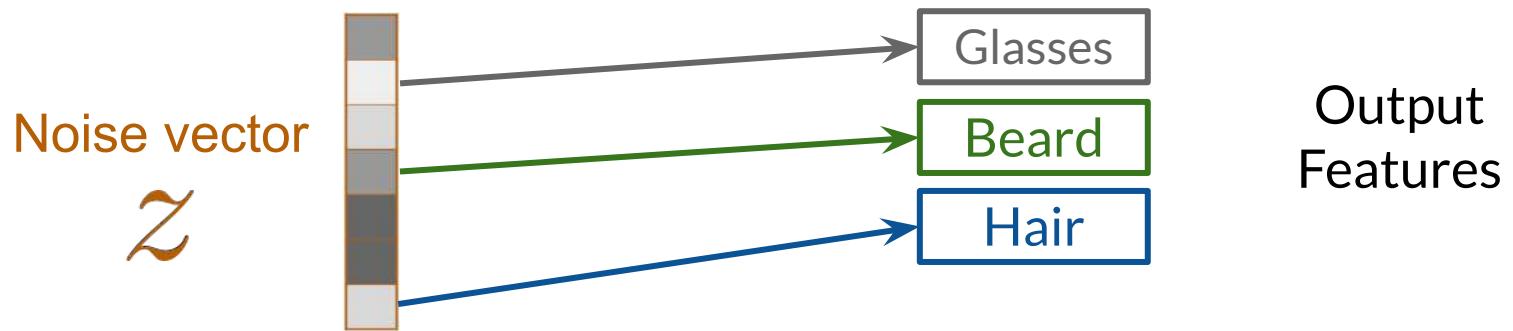


# Disentangled Z-Space



Changes to one feature  
don't affect the others

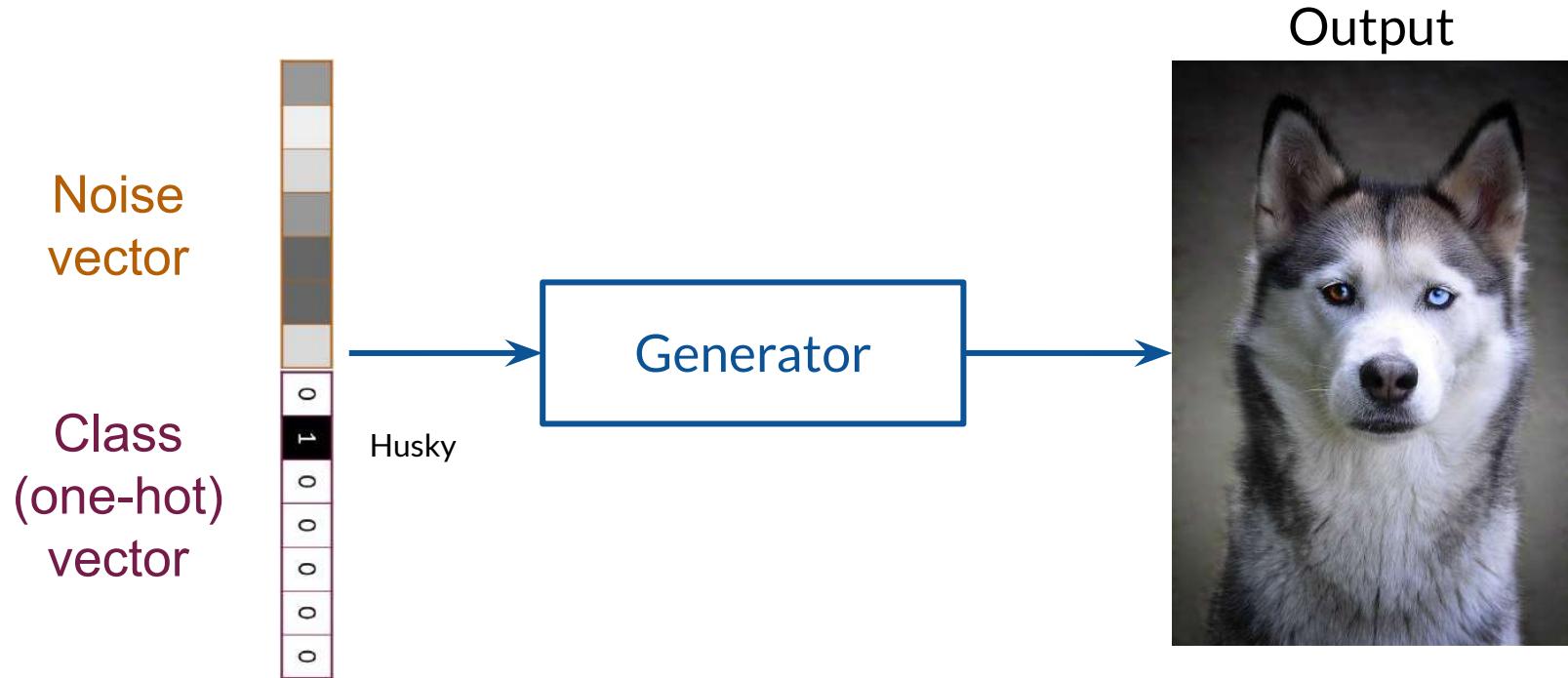
# Disentangled Z-Space



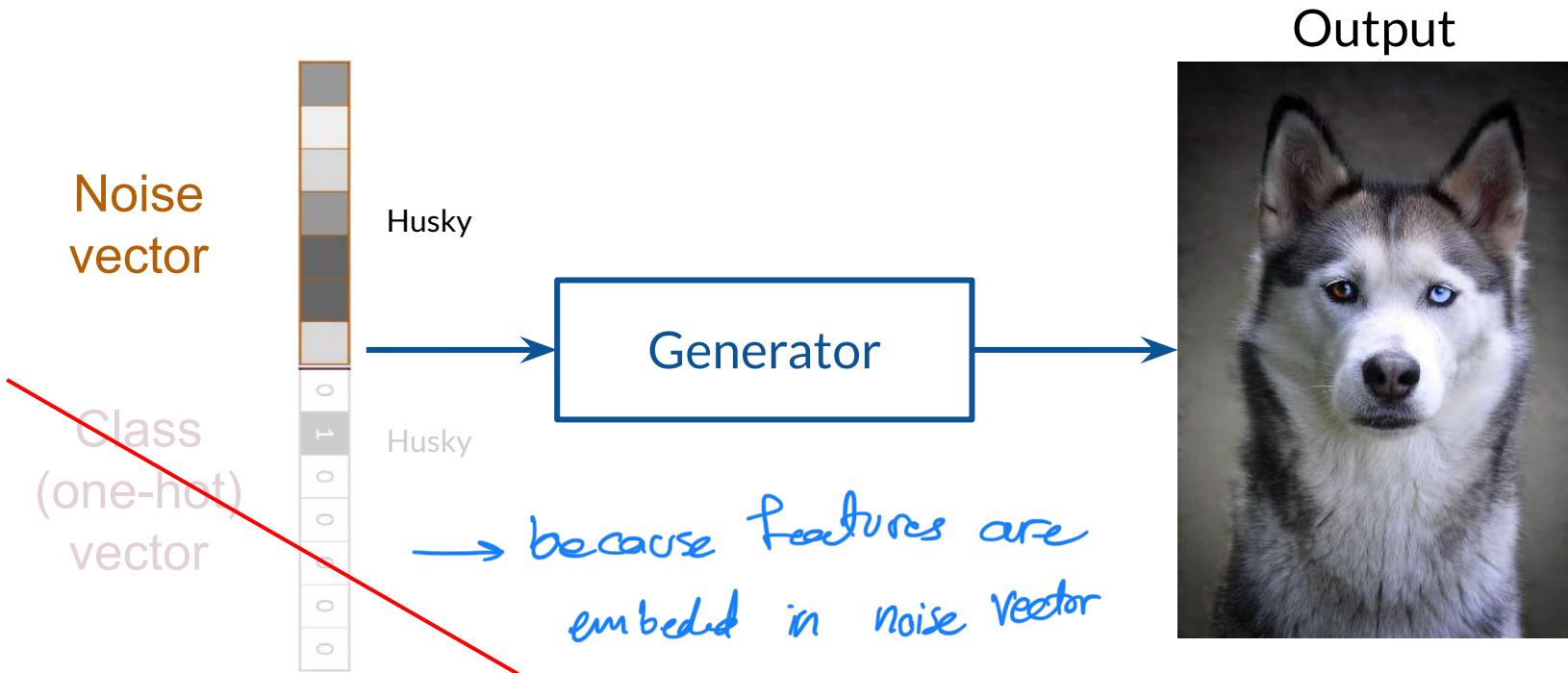
Changes to one feature  
don't affect the others



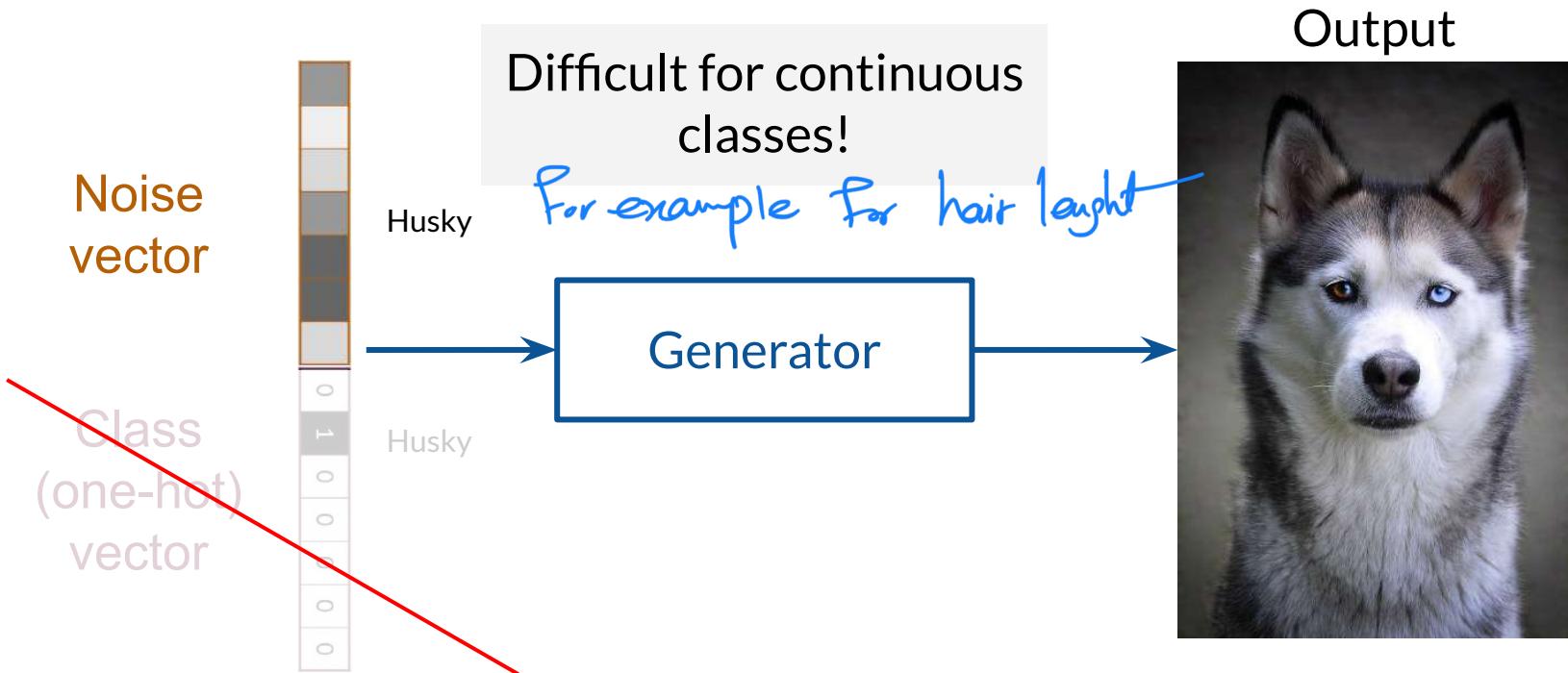
# Encourage Disentanglement: Supervision



# Encourage Disentanglement: Supervision



# Encourage Disentanglement: Supervision



# Encourage Disentanglement: Loss Function

$$v_1 = [1, 2, 3, \dots]$$

$$v_2 = [5, 6, 7, \dots]$$

# Encourage Disentanglement: Loss Function

$$v_1 = [1, 2, 3, \dots]$$

$$v_2 = [5, 6, 7, \dots]$$

$$L_{\text{new}} = L_{\text{original}} + \text{reg}_d$$

The diagram illustrates the formula for the new loss function. It shows the sum of two terms:  $L_{\text{original}}$  and  $\text{reg}_d$ . The term  $L_{\text{original}}$  is enclosed in a green box and has a green arrow pointing down to the text "Original loss". The term  $\text{reg}_d$  is enclosed in an orange box and has an orange arrow pointing down to the text "Regularization".

Original loss      Regularization

# Encourage Disentanglement: Loss Function

$$v_1 = [1, 2, 3, \dots]$$

$$v_2 = [5, 6, 7, \dots]$$

$$L_{\text{new}} = L_{\text{original}} + \text{reg}_d$$

Original loss      Regularization

Can be any loss function  
(e.g. BCE, W-Loss)

# Encourage Disentanglement: Loss Function

$$\begin{aligned} z_1 & \quad z_2 \\ v_1 = [ & \textcolor{pink}{1}, \textcolor{lightblue}{2}, 3, \dots ] \\ v_2 = [ & \textcolor{pink}{5}, \textcolor{lightblue}{6}, 7, \dots ] \end{aligned}$$

$$L_{\text{new}} = \boxed{L_{\text{original}}} + \boxed{\text{reg}_d}$$

Original loss      Regularization

Can be any loss function  
(e.g. BCE, W-Loss)

Q

# Encourage Disentanglement: Loss Function

$$\begin{aligned} z_1 & \quad z_2 \\ v_1 = [ & \quad 1, \quad 2, \quad 3, \dots ] \\ v_2 = [ & \quad 5, \quad 6, \quad 7, \dots ] \end{aligned}$$

Output feature #1      Output feature #2

$$L_{\text{new}} = \boxed{L_{\text{original}}} + \boxed{\text{reg}_d}$$

Original loss      Regularization

Can be any loss function  
(e.g. BCE, W-Loss)

# Summary

- Disentangled Z-spaces let you control individual features by corresponding z values directly to them
- There are supervised and unsupervised methods to achieve disentanglement

