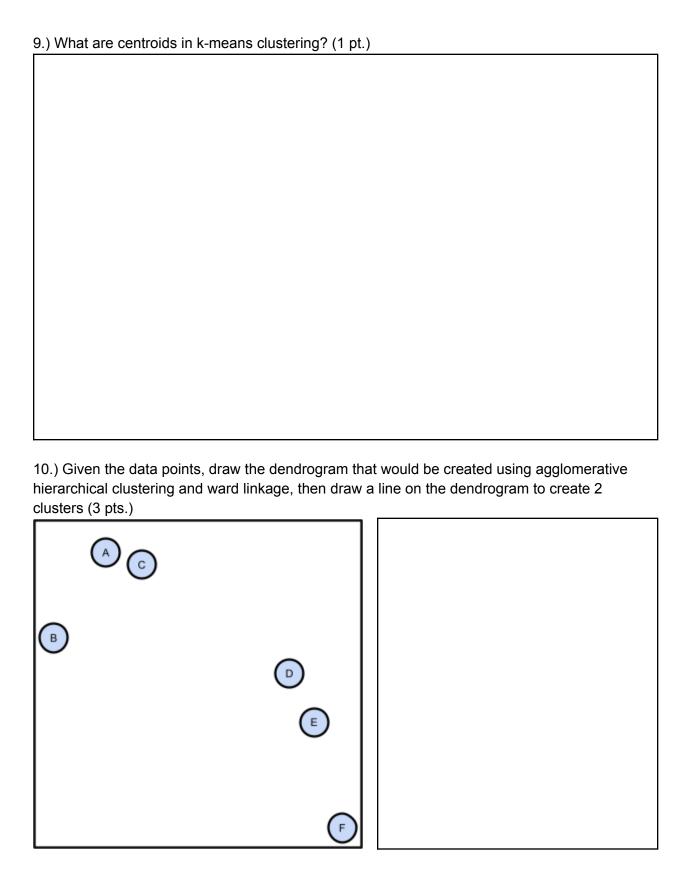
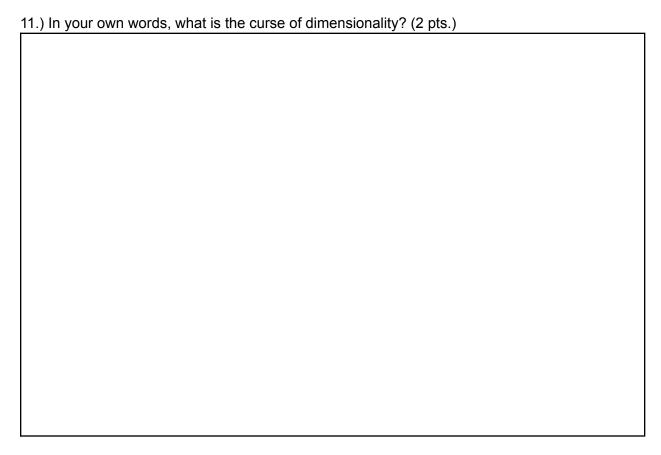
Name:
NetID:
0.) Practice packet submission (5 pts.)
1.) How are gradient descent and backprop related? (2 pt.)
2.) What is the difference between a regression task and a classification task? Give a real-world example of each (3 pts.)
2) When may we profes a soft margin electifier over a hard margin electifier 2 (1 pt.)
3.) When may we prefer a soft-margin classifier over a hard-margin classifier? (1 pt.)

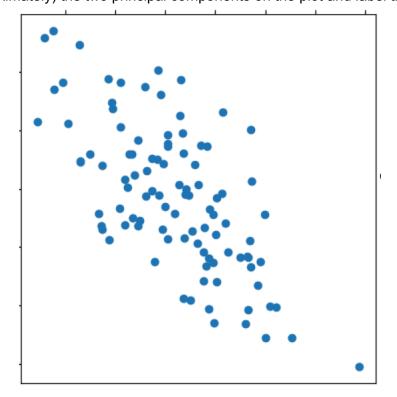
4.) What happens if you were to change the location of a support vector? (1 pt.)
5.) What is the kernel trick? (2 pts.)
6.) Why don't we typically use gradient descent for linear regressions? (2 pts.)

7.) What is the gradient we're descending when we use gradient descent? What are we trying optimize and what do we take the partial derivatives with respect to to do so? (3 pts.)	to
8.) What are the differences between supervised and unsupervised learning? (2 pts.)	



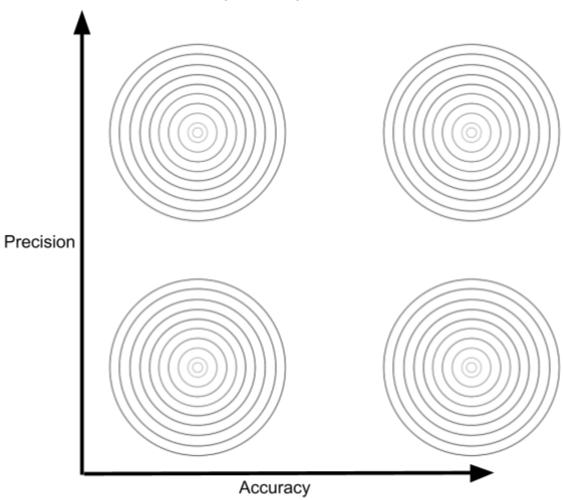


12.) Draw (approximately) the two principal components on the plot and label them (2 pts.)



13.) Why are the principal components always orthogonal to each othe the covariance matrix to ensure this happens? (2 pts.)	r? What do w	e do with
. С.		
14.) Given the following results, label each as Type 1 or Type 2 error (N	Multiple Choic	e) (5 pts.)
Result	Type 1	Type 2
Your twin is allowed through TSA with your ID		
You are diagnosed with a rare disease but you don't have it		
A rescue victim is declared dead but is actually alive		
There's a fire in the building but the alarm doesn't go off		
You reject the null hypothesis when it's actually true		

15.) Draw Xs on each of the four targets relating to their position on the X and Y axes (4 pts.)



16.) Write the following statement (1 pt.)

Tillust always split my data into training a	and testing and must not train on the testing data

17.) Given the pytorch code below, answer the following questions. Please refer to the loss and activation functions lookup table on the next page.

```
# Define the neural network
class SimpleNN(nn.Module):
    def __init__(self):
        super(SimpleNN, self).__init__()
        self.hidden = nn.Linear(3, 2)
        self.output = nn.Linear(2, 1)

def forward(self, x):
        hidden = self.hidden(x)
        out = self.output(hidden)
        sig = torch.sigmoid(sig)
        return hidden, out, sig

# Initialize the model, loss, and optimizer
model = SimpleNN()
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

a.) Draw the computation graph for the network. (4 pts.)

b.) Give the derivative chain for calculating the gradient of the bias in the first layer. (4 pts.)
= □b

and a quantum ye	u'd use to actually	- carcarate the gre	idionio. (Tpto.)	

Name	Plot	Equation	Derivative
Identity		f(x)=x	f'(x)=1
Binary step		$f(x) = egin{cases} 0 & ext{for } x < 0 \ 1 & ext{for } x \geq 0 \end{cases}$	$f'(x) = egin{cases} 0 & ext{for } x eq 0 \ ? & ext{for } x = 0 \end{cases}$
Logistic (a.k.a. Sigmoid or Soft step)		$f(x) = \sigma(x) = \frac{1}{1 + e^{-x}}$	f'(x)=f(x)(1-f(x))
TanH		$f(x)= anh(x)=rac{(e^x-e^{-x})}{(e^x+e^{-x})}$	$f'(x)=1-f(x)^2$
ElliotSig Softsign		$f(x) = \frac{x}{1+ x }$	$f'(x)=\frac{1}{(1+ x)^2}$

Name	Equation	Derivative
Mean Squared Error (MSE)	$\mathcal{L} = \frac{1}{n} \sum (y - \hat{y})^2$	$\frac{\partial \mathcal{L}}{\partial \hat{y}} = -2(y - \hat{y})$
Mean Absolute Error (MAE)	$\mathcal{L} = \frac{1}{n} \sum y - \hat{y} $	$\frac{\partial \mathcal{L}}{\partial \hat{y}} = -\operatorname{sign}(y - \hat{y})$
Huber Loss	$L = 0.5(y - \hat{y})^2$ if $ y - \hat{y} \le \delta$; else $\delta(y - \hat{y} - 0.5\delta)$	Piecewise gradient
Binary Cross Entropy (BCE)	$\mathcal{L} = -\left[y\log(\hat{y}) + (1-y)\log(1-\hat{y})\right]$	$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \frac{\hat{y} - y}{\hat{y}(1 - \hat{y})}$
BCE with Sigmoid	$\mathcal{L} = -\left[y\log(\sigma(z)) + (1-y)\log(1-\sigma(z))\right]$	$\frac{\partial \mathcal{L}}{\partial z} = \sigma(z) - y$
Categorical Cross Entropy	$\mathcal{L} = -\sum_{i} y_{i} \log(\hat{y}_{i})$	$\frac{\partial \mathcal{L}}{\partial \hat{y}_j} = \hat{y}_j - y_j$
KL Divergence	$\mathcal{L} = \sum y \log \left(\frac{y}{\bar{y}} \right)$	$\frac{\partial \mathcal{L}}{\partial \hat{y}} = -\frac{y}{\hat{y}}$
Poisson Loss	$\mathcal{L} = \hat{y} - y \log(\hat{y})$	$\frac{\partial \mathcal{L}}{\partial \hat{y}} = 1 - \frac{y}{\hat{y}}$

Answer the following questions about homework03, which was using clustering and SVMs for image segmentation.
18.) What is image segmentation? (2 pt.)
19.) Training the SVMs was very very slow, even after using PCA. Why do you think that is?
What properties about the SVM model result in a quadratic complexity? (3 pts.)

20.) For the SVM, we created features for our image (using the default patch size of 5) resulting in a (249900, 78) training matrix. How was that 78 calculated? Spitball some ideas for features that could have been better for our image than what we did. (2 pts.)
and obtain have been bester in each manage tries.
Bonus.) I've tried to show more code in class, but I mostly just kind of read over it and run it. Do you think it'd be more useful for you if we wrote some of it instead of just reading? (1 bonus pt.)
Bonus.) I've tried to show more code in class, but I mostly just kind of read over it and run it. Do you think it'd be more useful for you if we wrote some of it instead of just reading? (1 bonus pt.)