George received 90% Latest Submission Grade e80% To pass 80% or higher Solota next item Anomally detection Dear Mode 2,155 Milest 100 data paints of computers for computers in a data cores are residuationing. What type of algorithm should you use? To use the liditing a system to detectif computers in a data cores are residuationing. What type of algorithm should you use? Solota next declarating Correct Covering an accomply detection model does not require labeled@fifthe 81% by the residuation of the region of computers for a data paints of computers for computers in allowed coining. What type of algorithm should you use? They are faulding a system to detectif computers in a data core or we remains the core of the state of the received of the state of the received of the state of the received of the state of the state of the received of the state of the state of the state of the received of the rece	1/1 point
Go to next item Go to next item Go to next	1/1point
Anomaly detection Submit your assignment	1/1point
Now are building a system to detect if computers in a data center are malfunctioning. You have 10,000 data points of computers functioning well, and no data from computers malfunctioning. What type of algorithm should you use? A normally detection Supervised families Your grade Now are building a system to detect if computers in a data center are malfunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? Your grade Now are building a system to detect if computers in a data center are malfunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? You are building a system to detect if computers in a data center are malfunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? A normally detection Supervised families Or correct Or correct Use it during training by fitting one Guassian model to the normal engines, and a different Guassian model to the anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Guassian model to the normal engines, and a different Guassian model to the anomalous engines to evaluate your anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of bench normal an anomalous engines, only is an anomaly detection. Use supervised learning instead. Put the data of anomalous engines (singularly with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct A normally detection flags a new input x as an anomaly if p(x) < e. If we reduce the value of e, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is more likely to classify rewer examples as an ano	1/1 point
Pose Fieb 25,11.59 PM CCT You are building a system to detect if computers in a data center are millivactioning. You have 10,000 data points of computers functioning well, and no data from computers malfunctioning. What type of algorithm should you use? Normaly detection Pose	1/1 point
**Supervised learning	
Proceive grade Creating an anomaly detection model does not require labele® Bask 90% or higher Your grade 80% You are building a system to detect if computers in a data center are reallunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? You are building a system to detect if computers in a data center are reallunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? You are building a system to detect if computers in a data center are reallunctioning. You have 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use the 15 computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should well and 10,000 data points of computers malfunctioning. What type of algorithm should well and 10,000 data points of computers malfunctioning. What type of algorithm should well and 10,000 data points of computers malfunctioning. What type of algorithm should well and 10,000 data p	
Correct Creating an anomaly detection model does not require label@€@€®€® 10% or higher You grade 80% You are building a system to detect if computers in a data center are malfunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? You have so well dearning O correct You have a sufficient number of anomalous examples to build a supervised learning model. Supervised learning Use it during training by fitting one clausalan model to the normal engines, and at 6 meannalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one clausalan model to the normal engines, and a different clausalan model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning signifitm. Decause you have data of both normal and anomalous engines, soft ruse anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. O correct Anomaly detection flags a new input z as an anomaly if p(x) < c. If we reduce the value of c, what happens? The alignrithm is more likely to classify new examples as an anomaly. The alignrithm is less likely to classify new examples as an anomaly. The alignrithm will automatically choose parameters μ and σ to decrease μ(x) and compensate. In the lagrithm will automatically choose parameters μ and σ to decrease μ(x) and compensate.	
Your grade 80% You are building a system to detect if computers in a data center are maifunctioning. You have 10,000 data points of computers functioning well, and 10,000 data points of computers maifunctioning. What type of algorithm should you use? Anomaly detection Supervised learning Correct Subsequence Supervised learning Use it during training by fitting one Gaussian model to the normal engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You carnot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input z as an anomaly if $p(x) < \epsilon$. If we reduce the value of ϵ , what happens? The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The lagorithm is more likely to classify some examples as an anomaly. The classification and or the example as an anomaly.	
Two are building a system to detect if computers in a data center are malfunctioning, You have 10,000 data points of computers functioning well, and 10,000 data points of computers malfunctioning. What type of algorithm should you use? We keep your highest score Supervised learning Orrect You have a sufficient number of anomalous examples to build a supervised learning model. Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You have a data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomalous examples are wingut <i>x</i> as an anomaly if <i>p(x)</i> < <i>c</i> . if we reduce the value of <i>c</i> , what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is nore likely to classify new examples as an anomaly. The algorithm is more likely to classify new examples as an anomaly, and less likely to classify some examples as an anomaly. The algorithm is more likely to classify new examples as an anomaly, and less likely to classify some examples as an anomaly. The algorithm is more likely to classify new examples as an anomaly, and compensate. So incorrect	
Supervised learning Ocorrect Supervised learning Like Supervised learning Like Supervised learning Like Supervised learning Like Supervised learning Use it during training by fitting one Gaussian model to the normal engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and adliferent Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input x as an anomaly if p(x) < ε. if we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is more likely to classify new examples as an anomaly. The algorithm will automatically choose parameters μ and σ to decrease p(x) and compensate. In the algorithm will automatically choose parameters μ and σ to decrease p(x) and compensate.	1/1 point
Supervised learning Ocrrect You have a sufficient number of anomalous examples to build a supervised learning model. Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines, How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input <i>x</i> as an anomaly if <i>p</i> (<i>x</i>) < <i>c</i> . If we reduce the value of <i>c</i> , what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm will automatically choose parameters <i>µ</i> and <i>σ</i> to decrease <i>p</i> (<i>x</i>) and compensate. Noterect	
 Correct \(\triangle \) Like \(\triangle \) Distilke \(\triangle \) Report an issue You have a sufficient number of anomalous examples to build a supervised learning model. Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? \(\triangle \) Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. \(\triangle \) You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. \(\triangle \) Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. \(\triangle \) Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. \(\triangle \) Correct Anomaly detection flags a new input \(x \) as an anomaly if \(p(x) < \in \text{.} \) (e. If we reduce the value of \(\varphi\), what happens? \(\triangle \) The algorithm is more likely to classify new examples as an anomaly. \(\triangle \) The algorithm is less likely to classify new examples as an anomaly. \(\triangle \) The algorithm is more likely to classify new examples as an anomaly. and less likely to classify some examples as an anomaly. It depends on the example \(x\). \(\triangle \) The algorithm is more likely to classify new examples as an anomaly. and less likely to classify some examples as an anomaly. It depends on the example \(x\). \(\triangle \) The algorithm is more likely to classify some examples as an anomaly. and compensate. \(\triangle \) Incorrect 	
You have a sufficient number of anomalous examples to build a supervised learning model. Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input <i>x</i> as an anomaly if $p(x) < \epsilon$. If we reduce the value of ϵ , what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example <i>x</i> . The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate.	
Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input <i>x</i> as an anomaly if <i>p(x)</i> < ε. If we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify new examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example <i>x</i> . The algorithm will automatically choose parameters <i>μ</i> and <i>σ</i> to decrease <i>p(x)</i> and compensate.	
Say you have 5,000 examples of normal airplane engines, and 15 examples of anomalous engines. How would you use the 15 examples of anomalous engines to evaluate your anomaly detection algorithm? Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input <i>x</i> as an anomaly if <i>p</i> (<i>x</i>) < ε. If we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify some examples as an anomaly. and less likely to classify some examples as an anomaly. It depends on the example <i>x</i> . The algorithm will automatically choose parameters <i>μ</i> and <i>σ</i> to decrease <i>p</i> (<i>x</i>) and compensate. Note that the anomalous engines to evaluate your anomaly detection algorithm? The algorithm will automatically choose parameters <i>μ</i> and <i>σ</i> to decrease <i>p</i> (<i>x</i>) and compensate.	
 Use it during training by fitting one Gaussian model to the normal engines, and a different Gaussian model to the anomalous engines. You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input <i>x</i> as an anomaly if <i>p(x)</i> < ε. If we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example <i>x</i>. The algorithm will automatically choose parameters <i>μ</i> and <i>σ</i> to decrease <i>p(x)</i> and compensate. Incorrect 	1/1 point
 You cannot evaluate an anomaly detection algorithm because it is an unsupervised learning algorithm. Because you have data of both normal and anomalous engines, don't use anomaly detection. Use supervised learning instead. Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input x as an anomaly if p(x) < ε. If we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x. The algorithm will automatically choose parameters μ and σ to decrease p(x) and compensate. Incorrect 	
 Put the data of anomalous engines (together with some normal engines) in the cross-validation and/or test sets to measure if the learned model can correctly detect anomalous engines. Correct Anomalous examples are used to evaluate rather than train the model. Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input x as an anomaly if p(x) < ε. If we reduce the value of ε, what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x. The algorithm will automatically choose parameters μ and σ to decrease p(x) and compensate. Incorrect 	
Correct Anomalous examples are used to evaluate rather than train the model. Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input x as an anomaly if $p(x) < \epsilon$. If we reduce the value of ϵ , what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate. Incorrect	
Anomalous examples are used to evaluate rather than train the model. Anomaly detection flags a new input x as an anomaly if $p(x) < \epsilon$. If we reduce the value of ϵ , what happens? The algorithm is more likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x . The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate.	
 The algorithm is more likely to classify new examples as an anomaly. The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x. The algorithm will automatically choose parameters μ and σ to decrease p(x) and compensate. Incorrect 	
The algorithm is less likely to classify new examples as an anomaly. The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x . The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate.	0/1 point
 The algorithm is more likely to classify some examples as an anomaly, and less likely to classify some examples as an anomaly. It depends on the example x. The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate. Incorrect 	
\bigcirc The algorithm will automatically choose parameters μ and σ to decrease $p(x)$ and compensate. \bigcirc Incorrect	
⊗ Incorrect	
5. You are monitoring the temperature and vibration intensity on newly manufactured aircraft engines. You have measured 100 engines and fit the Gaussian model described in the video lectures to the data. The 100 examples and the	
resulting distributions are shown in the figure below.	1/1 point
The measurements on the latest engine you are testing have a temperature of 17.5 and a vibration intensity of 48. These are shown in magenta on the figure below. What is the probability of an engine having these two measurements?	
temperature vibration	
0.03000	
0.0738	
0.0600	
$\begin{pmatrix} \hat{x} \\ \hat{x} \end{pmatrix}_{0.01500}$	
0.0400	
0.01000	
0.0200	
0.0000 ** * * * * * * * * * * * * * * *	
10.0 15.0 17.5 20.0 25.0 30.0 20 40 48 60 80 X ₁	
O 0.0339 1.003390 - 0.0000	
○ 0.0738 + 0.02288 = 0.0966 ○ 17.5 * 48 = 840	
● 0.0738 * 0.02288 = 0.00169	
O 17.5+48=65.5	
○ Correct According to the model described in lecture, p(A, B) = p(A) * p(B).	
On the Second Se	

1 of 1 6/19/2024, 11:00 AM