		capture context (e.g., time of day) none of the above		
1 point	2.	Recommending items using a classification approach can (<i>check all that apply</i>): provide personalization capture context (e.g., time of day) none of the above		
1 point	3.	Recommending items using a simple count based co-occurrence matrix can (check all that apply): provide personalization capture context (e.g., time of day) none of the above		
1 point	4.	Recommending items using featurized matrix factorization can (check all that apply): provide personalization capture context (e.g., time of day) none of the above		
1 point	5.	Normalizing co-occurrence matrices is used primarily to account for: people who purchased many items items purchased by many people eliminating rare products none of the above		
1 point	6.		Feature vector (1.73, 0.01, 5.22) (0.03, 4.41, 2.05) (1.13, 0.89, 3.76)	
		Product ID 1 2 3 Product #1 Product #2 Product #3	Feature vector (3.29, 3.44, 3.67) (0.82, 9.71, 3.88) (8.34, 1.72, 0.02)	
1 point	7.	For the liked and recommended items displayed below, calculate the recall and round to 2 decimal points. (<i>As in the lesson, green squares indicate recommended items, magenta squares are liked items. Items not recommended are grayed out for clarity.) Note: enter your answer in American decimal format (e.g. enter 0.98, not 0,98)</i>		
1 point	8.	For the liked and recommended items displayed below, calculate the precision and round to 2 decimal points. (As in the lesson, green squares indicate recommended items, magenta squares are liked items. Items not recommended are grayed out for clarity.) Note: enter your answer in American decimal format (e.g. enter 0.98, not 0,98)		
1	9.	0.25 Based on the precision-recall	curves in the figure below, which recommender	
point		RecSys #1 RecSys #2 RecSys #3 recall		
		RecSys #1		

RecSys #2

RecSys #3

Recommending items based on **global popularity** can (*check all that apply*):

point