Recommender Systems Conceptual Assignment 1

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1. Basic Linear Algebra

Hand compute, X^T, $Tr(X), \|X\|_F, 2 \times X, X + I$ when,

$$X = \begin{bmatrix} 4 & -3 \\ -2 & 5 \end{bmatrix}$$

Show your work and also verify that you have the right answer through numpy computations in python.

2. Basic Linear Algebra

Let X be as in problem 1 and I be the identity matrix. Hand compute the Frobenius norm of $X - I$. Also verify your result through numpy computations for the same in python.

3. SVD and Truncated SVD

Consider the data matrix,

$$Z = \begin{bmatrix} 4 & -3 & -1 \\ -2 & 5 & 2 \\ 8 & -6 & -1 \end{bmatrix}$$

In numpy, compute the SVD of Z. Truncate the SVD to 2 singular values and get a rank-2 approximation of Z, call it Z_2. Find the relative error between Z and Z_2, i.e. $\frac{\|Z - Z_2\|_F}{\|Z\|_F}$ where $\|.\|_F$ refers to the Frobenius norm. Does the magnitude of the error make sense to you and why? Show your complete code in your solution. *Why is truncated SVD useful in machine learning? Often times, truncating SVD to a few factors, gives a compressed representation to the information stored in the matrix. It also helps understand which singular vectors are important in representing the data.*

4. Cosine Similarity

Consider two vectors, x and y. When is the dot product between x and y equal to the cosine similarity between x and y? Pick all options that apply:

1. When x has a norm of 1
2. When both x and y have a norm of 1
3. When y has a norm of 1
4. When $x = y$

5. Cosine Similarity

Let consumer products be represented by vectors in 100 dimensions (e.g. p_i for product i). Customers who buy product 50, almost always never buy product 100. On the other hand, customers who buy product 50 sometimes buy product 90 and sometimes don't. What cosine-similarity relationships between the products best describes the situation:

1. $\cos(p_{50}, p_{90})$ equals 1 and $\cos(p_{50}, p_{100})$ equals -1
2. $\cos(p_{50}, p_{90})$ equals -1 and $\cos(p_{50}, p_{100})$ equals 1
3. $\cos(p_{50}, p_{90})$ equals 0 and $\cos(p_{50}, p_{100})$ equals 1
4. $\cos(p_{50}, p_{90})$ equals 0 and $\cos(p_{50}, p_{100})$ equals -1

6. New products

Let's say there are 10 new fashion dresses that just got released to Samabazon's shopping website. You are responsible for surfacing these new products to interested customers. You develop a "new products recommendation" ML model to do this. After deploying the model, some of the customers have sent a feedback stating that they are getting fashion recommendations that are not even a right fit (and sometime inappropriate). What might have gone wrong with your deployed model? Pick all options that apply.

1. Nothing - There will always be some negative feedback
2. It maybe that the model isn't gender sensitive or specific?
3. It maybe that the model has better fashion sense than the customer?
4. It maybe that the model isn't picking on the right customers due to an issue with similarity metric?

7. Precision and Recall

Precision and Recall are two of the most important metrics to measure goodness of a recommender system. There is also precision at k and recall at k, variations on these two metrics. In an offline test data set context for product purchase data: Precision refers to percentage of your recommendations that you got right. Recall refers to percentage of customer purchases that you recommended Let's say that you have two customers with following past purchases: { apples, paper towels, phone charger, speakers } and { granola bars, pens, microphone, ring light }. Your model's recommendations for the two customers were respectively, {oranges, phone charger, microphone } and { pens, microphone, apples }. What would be your model's average precision and average recall (averaged over the two customers):

1. 0.5 and 0.38
2. 0.3 and 0.5
3. 0.38 and 0.5
4. 0.5 and 0.3

8. Internal Testing

You built a recommender system for Sambazon products. It turns out all your recommendations (predictions) in your offline test data set were mostly past purchases by the customers, meaning your model seems to be recommending relevant items. However, when you did an internal team test with your new recommender system, your colleagues mentioned in feedback that they are not getting relevant recommendations in some cases (based on some dummy purchases they made to build their specific customer profile). What might have gone wrong? Pick all that apply:

1. You measured precision, did you check recall?
2. You surely made a mistake in the modeling process (maybe pick a better ML model)
3. Your training data didn't have coverage for some of the dummy purchases
4. You measured recall, did you check precision?