Performance of Covariance Neural Networks on Rating Prediction

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1. Background

Covariance Matrix: a square matrix summarizing the second-order relationships of different variables

$Cov(u_1, u_1)$	$Cov(u_1, u_2)$	$Cov(u_1, u_3)$	$Cov(u_1, u_4)$
$Cov(u_2, u_1)$	$Cov(u_2, u_2)$	$Cov(u_2, u_3)$	$Cov(u_2, u_4)$
$Cov(u_3, u_1)$	$Cov(u_3, u_2)$	$Cov(u_3, u_3)$	$Cov(u_3, u_4)$
$Cov(u_4, u_1)$	$Cov(u_4, u_2)$	$Cov(u_4, u_3)$	$Cov(u_4, u_4)$

Covariance measures **dependence between two variables**, showing how one variable changes with another.

We can use this to **model underlying relationships** between users and items for collaborative filtering

2. Research Questions

1. How do VNNs perform on rating prediction tasks using the covariance matrix as the GSO?
2. How are VNNs affected by perturbations in their graph structure?

Hypothesis: VNNs will perform better than first-order models thanks to the high sparsity of the dataset.

3. Methodology

Dataset

MovieLens 100k

movielens

Evaluation Metric

Truth

Prediction

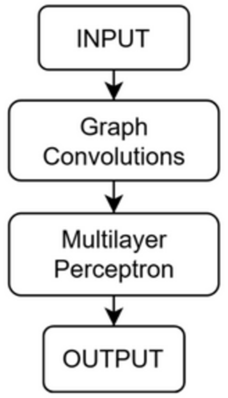
$$\sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}}$$

Number of Samples

RMSE

Pipeline

1. Compute the **covariance matrix** from training data. Use this for the model's **Graph Shift Operator (GSO)**
2. **Mask values** from the interaction matrix. Use these masked values for evaluation, and the remainder for forward passes.
3. **Train** the model.
4. **Evaluate** on the **test set.**



The VNN Architecture

Experiments

Robustness

Force the model to use only a sample of the training data to create the GSO, then train the model and evaluate its performance

Stability

Introduce perturbations into the GSO of a trained model and evaluate its performance

4. Results

Final Model Performance:

0.9682, std. dev of 0.00553

Comparison to Baselines

Model	RMSE
VNN	0.9682
Global Mean	1.1537
Random	1.8762
Identity GSO	1.0695
All-ones GSO	0.9823

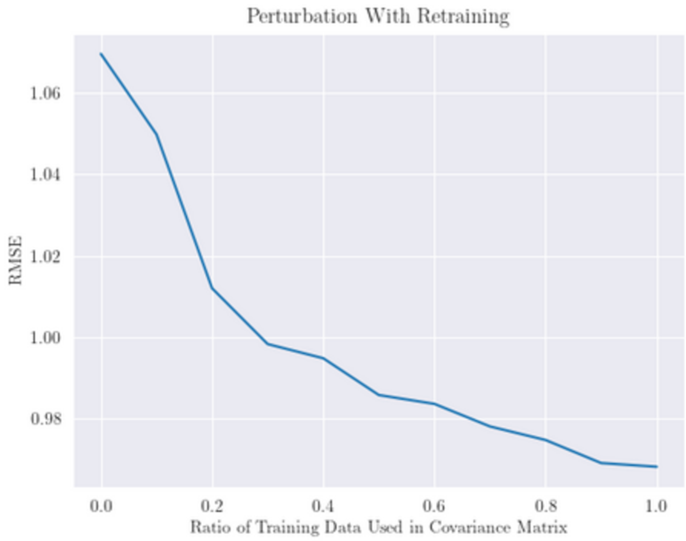
The VNN is able to beat the baseline models, demonstrating that it is **properly learning.**

Comparison to Other Models

Model	RMSE
VNN	0.9682
MC	0.973
IMC	1.653
GMC	0.996
GRALS	0.945
sRGCNN	0.929
GC-MC	0.905

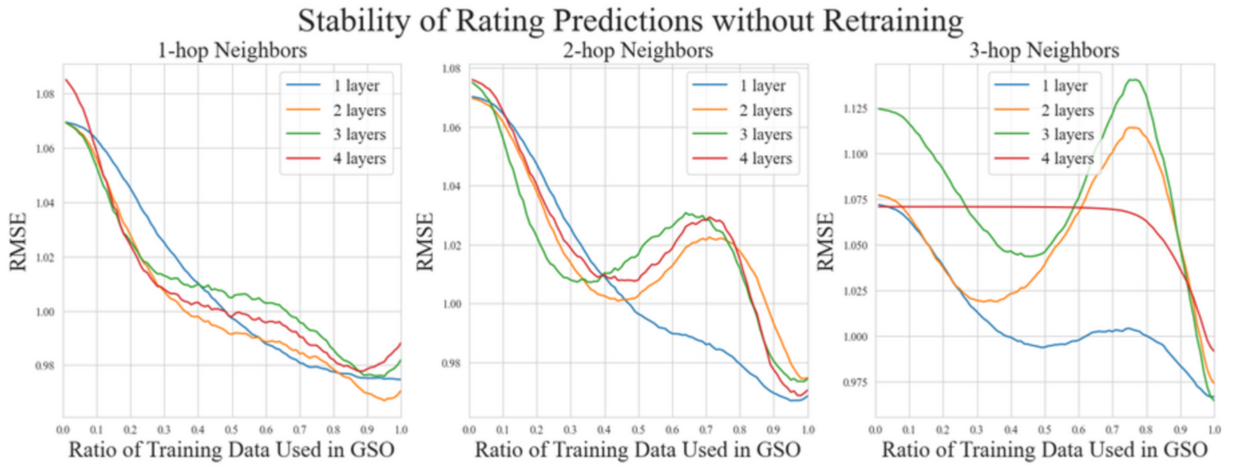
While able to **beat simpler matrix completion models**, the VNN **struggles to beat more advanced models** that are able to grasp more relationships.

Robustness Experiment Results



The VNN's performance degrades as the covariance matrix is perturbated, implying the model **learns second-order relationships**.

Stability Experiment Results



The model's performance **decreases gradually for the 1-hop VNN**, no matter how many layers. These display **relatively stable performance when compared to the 2-hop and 3-hop VNNs**. This is most likely due to **oversmoothing**. As the network gets deeper, the effects become more exaggerated.

5. Conclusions and Limitations

Conclusion

1. VNNs are capable of performing strongly in rating prediction tasks by leveraging second-order relationships using the covariance matrix.
2. The stability of VNNs depend on the density of the network and may be prone to oversmoothing.

Limitations

- Transductive Pipeline
- Dataset may be too sparse, so covariance estimate may be too noisy

Future Work

- Combine Architectures
- Better Imputation
- Regularization to overcome oversmoothing

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