Paper 7 - Collaborative Feature Learning from Social Media

Idea -

- Learning Image Feature Representations. This uses a data-driven feature learning process which does not use category labels.
- Learn from User behaviour data to guide the image learning process. - This is the image relationship discovered in the latent space from the user behaviour data.
- This work helps learn better image similarity features.
- The work outperforms SOTA features on tasks such as finding images of simar styles. (Again the problem here is that style is not defined concretely)

Problems with Hand-crafted features -

- These features require significant amount of domain knowledge, and
- donot generalize well to new domains.

Problems with Data Labels -

- Collecting large labeled datasets is not an easy task even with the help of crowdsourcing.

Maybe overcome using **unsupervised** methods of learning and/or **transfer learning.**

Getting Social Media into the Picture -

- Prior that 2 photographs viewed / pinned / liked by the same user are of similar style.
- Aggregate the user behaviour data across many users. Eg- The photos liked by a group of users of similar interests tend to have very similar styles.
- Use the user behaviour data collected on social media to recover latent representations of individual images and learn a feature transformation from images to the recovered latent representations.

Challenges with user data -

- User Behaviour data can be very **noisy and sparse**.

Dataset-

- 1.9 Million images from Behance.net

Method -

- Get content item latent factors and user latent factors.
- Latent factors of content items encode rich information about the similarity between the content items.
- Get pseudo-classes by clustering their corresponding latent factors using K-Means.

Latent Factor Learning
Image Feature Learning with Pseudo Classes - using a DCNN
Image Similarity on Behance -

- Similarity between images are calculated using cosine similarity.
- Visually inspect the visual relationship between a large number of queries and their NNs. (Show a few randomly selected images)
- Quantitative Analysis - given a query image
    - The number of common viewers between the query and the retrieved NNs. Measure for each pair of query and NN, the ratio between their common viewers and the union (Set size) (Measure calculated for all top 100 NNs. Report it's mean across test set at every rank position)
    - The number of retrieved NNs that have been viewed by the owner of the query image. This quantity is measured between a query and all of the top 100 NNs. Report the average of this number across all queries in the test set.

Image Classification on Benchmarks -

- Use Caltech256 dataset for object classification.
- Get learnt features from model and other pre-trained features from ImageNet .
- Use an linear SVM as the classification model.