Why Board Games?
Interest in board games has grown dramatically. Releases have been increasing in the last years by about 25% each year:

![Graph showing board games released by year](image1)

Consumers can find it hard to choose a game and often rely on curated lists. Using qualitative and quantitative data, collected from board game community site "Boardgamegeek.com", we researched application of existing and novel techniques for recommending board games.

Evaluation Metrics
- **Precision@k** presents the fraction of the relevant games in the recommended set to the total number of games in the recommended set. $k$ is the number of retrieved items considered in this calculation.
- **Recall@k** is the fraction of relevant games in the recommended set compared to the total count of relevant games. $k$ determines the size of the recommended set.
- **Normalized Discounted Cumulative Gain (nDCG)** uses a graded relevance scale to attribute the usefulness of recommended results based on their rank. This gain is based on the position in the result list - results on the top have a higher usefulness.
- **Mean Average Precision (MAP)** is the mean of all Average Precisions (APs). The AP for a user is calculated as the average precision score from every recall value from 0 to 1.
- **Novelty and Diversity** measure how similar are recommendations to the historically liked items of a user, and among each other, respectively. They are essentially comparisons of boolean arrays in which the games’ mechanics and categories are represented.

Evaluation Results
The collaborative approaches give the best results regarding the ranking metrics **Precision@k, Recall@k, nDCG and MAP**. However, the content-based IDF approach appears to be performing the best when regarding **Novelty and Diversity**. Interestingly, the hybrid autoencoder approach does not improve over the non-content-aware autoencoders. This shows that ratings are a more expressive indicator of good recommendations.

Collaborative Filtering
- **User - User / Item - Item.** The basis of this approach is the computation of a similarity matrix of all users or games respectively. It uses mean-adjusted cosine similarity over the ratings of users/games to each other.
- **Matrix Factorization.** This approach embeds users and items in a low-dimensionality latent space. Training the model involves setting various hyperparameter values.
- **Autoencoder.** Autoencoders generalize matrix factorization in that they learn non-linear embeddings (for users, items or both) using neural networks.
- **Denoising Autoencoder.** A denoising autoencoder adds distortion to its input in order to learn more robust embeddings.
- **Variational Autoencoder.** The variational autoencoder learns a latent statistical model from the input data and learns its parameters during training.

Content Based Recommendation
- **k-Nearest-Neighbor.** The categories, mechanics and other attributes of a game are turned into a binary attribute vector. A distance calculation computes the similarity to other games, which are recommended.
- **IDF-based.** This method uses inverse document frequency. Games that share the same attributes are recommended. The rarer the attribute, the higher weighted they are.

Hybrid Approach
The hybrid autoencoder uses information about preferred mechanics, categories and other attributes (orange) in addition to the ratings of each user (blue). The intermediate layers (red, purple) are a reduced representation which is trained to match the output layer, consisting of the game ratings (green).