Design Recommendation

Unlike consumers, item makers/producers often face different kinds of questions:
- What new set of items would appeal to the widest possible number of customers (with different preferences)?
- How many items should we make?
- Which users would each item attract and how large is each of these user groups?
- We present a problem formalization and methodology to address these interrelated issues simultaneously.

PROBLEM FORMULATION

**Key Questions**

- Given:
  - Users $U = \{u_1, u_2, ..., u_M\}$
  - Set of all possible items $v \in S$
  - Rating function $r(u,v)$ and threshold $r$

- Find a set of novel items $V'$

$$\text{argmax}_{V'} \sum_{u \in U} \sum_{v \in V'} r(u,v) c_{uv},$$

subject to:

$$c_{uv} \in \{0,1\} \quad (\text{if } c_{uv} = 1 \text{ iff } r_{uv} > r)$$
$$\sum_{v \in V'} c_{uv} = 1 \quad \text{(each user covered by 1 item)}$$
$$|V'| = K \quad \text{(K items selected)}$$

**Problem:** How to solve since $S$ and $r$ unknown?

**Key Idea:**
- Leverage real-vector representations $z_v, z_u \in Z$ for users and items respectively, which are learnt using a convenient parametric rating function (e.g., $r = z_u^T z_v$).
- Search in $Z$ instead of $S$.

APPROACH & METHODS

Three steps:
1. Learn the latent representation $Z$ and encoder $f_u(x)$ and decoder $g_v(x)$.
2. Obtain set of novel items $z_v \in Z$ through greedy maximum coverage.
3. Generate novel item features using the decoder $g_v(x)$ for each $z_v \in Z$.

Two Models:
- Linear Model (LM) with linear encoder and decoder
- Variational Autoencoder (VAE) with neural networks.

If you’re in a hurry (TL;DR)
- We address the problem of **recommendation for item makers** instead of consumers: how can we generate a set of **new items** that appeals to a large number of people?
- We present a problem formalization based on **learned latent real-vector spaces**.
- We leverage **deep generative models** and greedy *maximum coverage* to generate plausible new items.

Experiments & Results

- **Validated model on a 20-dimensional synthetic dataset.**
- **Key Question:** Can we recreate the missing items?
- **Key Results:** Yes, to a good degree (low RMSE).
- VAE model outperforms LM model.

**Increasing coverage** of the users with $K$.
- Lower real coverage than predicted due to slightly biased rating prediction.

SYNTHETIC

- Applied Collaborative VAE model to MART abstract art dataset (500 art pieces, 10k ratings by 100 people)

**MOVIE TAG GENOMES**

- Five novel art pieces (left) with closest (reconstructed) existing artwork.
- Set covers 82% of the users at threshold $r = 0.9$
- Generated art is unique and diverse.
- Novel combination of forms and colors.

- Movelens Genome Generation (~4k movies, ~1 million ratings by 6k users).
- Each movie represented by 450 tags.

- Top 3 generated movie genomes (above) at threshold $r = 0.8$, with 3 closest existing movies (images)
- Diverse set of movies with high 95% coverage (84%, 72% and 36% independent coverage).
- 4th and 5th movies (not shown) are a drama about culture-clash and a visually-appealing sci-fi movie.

Future Work: What’s Next?

- Novel item creation under budget and other constraints.
- Complex item generation, e.g., 3D structures, food recipes.
- Collaborative Design with a Human-in-the-Loop.