# Capstone Project Writeup

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(Quietness is the Beginning of Virtue)

## Abstract

Current content delivery systems fail to utilize emotional statuses of users. We propose to build an emotionally intelligent content recommendation system. Users will choose their desired emotional state and the recommendation system will deliver an image that has a high likelihood of eliciting the desired emotion for that particular user. Our unlabeled training data will come from ImageNet, a database of over 10 million images tagged with words describing what is pictured. We will create labels for ImageNet by showing the images to users and record their (continuous) emotional response via Microsoft's Emotion API and user reported response.

We will choose which images to present to each user by utilizing several tools from active learning.

## Introduction

The current approaches to Content Delivery Systems (CDS) typically are based on either collaborative filtering, low rank matrix factorization methods, or on systems that impute user interest profiles based on content browsing behavior and retrieving items similar to the interest profiles.

The mechanics of our recommendation system will be traditional but the way to measure the user's feedback will be novel. We feel that directly measuring user's emotional state is a much better indicator of engagement than click through rate, likes or star rating. We choose to directly measure the user's emotional engagement over leaving the users to report it. The reason for this is there is a discrepancy between what people feel and what they report they feel. For example, users can misclick, are subject to social desirability bias (want to look good to their peers) or just don't want to participate in the reporting.

**Active Learning**

Our CDS will be based on active learning to cope with "a new user cold start" problem and to efficiently pick content to show to the user. Active learning is a special case of semi-supervised learning in which a learning algorithm is able to interactively query the user to obtain the desired labels at new data points[3][4]. In our case we will be presenting photos to users and user's emotional response will be measured using Microsoft's Emotion API. Our active learning model will intelligently choose which content to show a given user(s) and that can drastically cut down on the amount of data required to improve itself.

To get the labeled data we will utilize a number of possible strategies for picking an image to show to a user, a few of which are:

- If we train multiple models for our recommendation system, we can choose to show the image that the models disagree on the expected output (emotional response) the most. This is known as a query by committee.
- Label images that we are most uncertain about the emotional response from a particular user.
- Choose the image based on which will minimize output variance the most.
- Choose the image that will decrease the generalization error the most.

Later on when other users will be using our system we will need to create a balance between keeping our users engaged (showing them content that is likely to create their desired emotional response) and showing them content that is likely to improve our model's performance. There are a number of strategies for achieving this balance a few of which are:

- Designate a small proportion of the potential images to optimize model performance, the rest of the time optimize user engagement.
- This kind of problem can be viewed as the multi-armed contextual bandit problem[2][7]. Where the context is the desired emotional response and the reward is the recorded emotional response.

**Data Sets**

- ImageNet -http://image-net.org/ that we will enhance through our Active learning model and turn into Emotion Centric User Content Pair

**Build Plan**

**v0.1 (3–4 weeks)**

- Define subset of the ImageNet collection ~10k images based on descriptive tags
- Store all data in two local databases:
    - Images along with their meta-tags (what is in the image) as well as summary data on users emotional response to the image.
    - Each users history of emotional reactions to images presented to them
- Utilize Microsoft Emotion API for User State Classification API Docs
- Constrain possible emotions to anger, contempt, disgust, fear, happiness, neutral, sadness and surprise
- Create interface for user reported emotions (emoticons)
- Runs script locally
- Handles a single User
- Pull next pic
- Track time on a specific image

**v0.2 (2–3 weeks)**

- Users can request specific emotion
- Use pre-trained model ( from version 0.0 )
- Handles multiple users
- Runs from the browser (locally)
- Active Learning takes into account user engagement

**Other Possible Areas of Research**

1. Explore discrepancy between user reported emotions and emotions according to Microsoft API
2. Explore extent to which pictures have an inherent emotional quality
3. Extend content to video and text
4. Rank/visu images in terms of the strength and consistency of the emotional responses they generate

**References**

**Current State of the Art**


1. Zhong, Erheng, et al. "Building Discriminative User Profiles for Large-scale Content Recommendation." *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2015.
2. Bouneffouf, Djallel, et al. "Contextual bandit for active learning: Active thompson sampling."*International Conference on Neural Information Processing*. Springer International Publishing, 2014.
3. Settles, Burr. "Active learning literature survey." *University of Wisconsin, Madison* 52.55-66 (2010): 11.
4. **Jump up^** Rubens, Neil; Elahi, Mehdi; Sugiyama, Masashi; Kaplan, Dain (2016). "Active Learning in Recommender Systems". In Ricci, Francesco; Rokach, Lior; Shapira, Bracha. *Recommender Systems Handbook* (2 ed.). Springer US. ISBN 978-1-4899-7637-6.
5. DYNAMIC MULTIMEDIA CONTENT DELIVERY BASED ON REAL-TIME USER EMOTIONS
6. Salmeron, Jose L. "Fuzzy cognitive maps for artificial emotions forecasting." *Applied Soft Computing* 12.12 (2012): 3704-3710.

7. Li, Lihong, et al. "A contextual-bandit approach to personalized news article recommendation."*Proceedings of the 19th international conference on World wide web*. ACM, 2010.
8. Ciuk, David, Allison K. Troy, and Markera C. Jones. "Measuring Emotion: Self-Reports vs. Physiological Indicators." *Physiological Indicators (April 16, 2015)* (2015).
9. Basu, Kinjal, Shaunak Chatterjee, and Ankan Saha. "Constrained Multi-Slot Optimization for Ranking Recommendations." *arXiv preprint arXiv:1602.04391* (2016).
10. Lin, Kevin Hsin-Yih, Changhua Yang, and Hsin-Hsi Chen. "What emotions do news articles trigger in their readers?." *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 2007.
11. Li, Weiyuan, and Hua Xu. "Text-based emotion classification using emotion cause extraction."*Expert Systems with Applications* 41.4 (2014): 1742-1749.
12. Kozareva, Zornitsa, et al. "UA-ZBSA: a headline emotion classification through web information."*Proceedings of the 4th International Workshop on Semantic Evaluations*. Association for Computational Linguistics, 2007.
13. Quan, Xiaojun, et al. "Latent discriminative models for social emotion detection with emotional dependency." *ACM Transactions on Information Systems (TOIS)* 34.1 (2015): 2.
14. Alm, Cecilia Ovesdotter, Dan Roth, and Richard Sproat. "Emotions from text: machine learning for text-based emotion prediction." *Proceedings of the conference on human language technology and empirical methods in natural language processing*. Association for Computational Linguistics, 2005.
15. Ciuk, David, Allison K. Troy, and Markera C. Jones. "Measuring Emotion: Self-Reports vs. Physiological Indicators." *Physiological Indicators (April 16, 2015)* (2015).