Modeling Temporal Evolution in the Endomondo Fitness Data Set

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ABSTRACT

1. INTRODUCTION

In order to

2. MOTIVATION

3. RELATED WORK

[1] describes various models which account for temporal evolution of user expertise through online reviews on websites such as Amazon, BeerAdvocate, RateBeer, CellarTracker.

4. ENDOMONDO FITNESS DATA SET

In this section, we introduce the Endomondo fitness data set. [?].

5. BASELINE MODEL

This section describes a baseline model to predict the duration of a workout given the distance.

6. TEMPORAL EVOLUTION OF USERS

This section describes a model that attempts to account for temporal evolution of users across workouts. First, we describe the model and then describe the training algorithm.

6.1 Model Specification

In order to account for evolution in the fitness level or capability of a user over time, we associate a *experience level* or *fitness level* e with each workout w. This can be seen as a way of encoding how fit the user is at the time of the workout w. The value e is an integer in the interval $[0, E)$ where E is the number of experience levels.

Intuitively, we expect the experience level of a user to either stay the same or increase with each workout. We encode this intuition in the form of a monotonicity constraint on the experience levels of workouts for each user, as given below:

$$\forall u, i, j \quad t_{ui} \geq t_{uj} \implies e_{ui} \geq e_{uj}$$

Then, given the total distance d_{ui} for the i'th workout of user u, the predicted duration T'_{ui} of the workout is given by:

$$T'_{ui} = (\alpha_{e_{ui}} + \alpha_{ue_{ui}})(\theta_0 + \theta_1 d_{ui})$$

where e_{ui} is the experience level of the user u at the i'th workout. Thus, we have one parameter α_{ue} per user u per experience level e. Further, we have an intercept term α_e for every experience level e, common to all users. The terms θ_0 and θ_1 are global to all users and experience levels. Thus, given U users and E experience levels, we have a total of $UE + E + 2$ parameters.

Note that setting $E = 1$ reduces the model to the baseline model described in section 5.

6.2 Training Algorithm

7. TEMPORAL EVOLUTION OF WORKOUTS

8. RESULTS

9. CONCLUSION AND FUTURE WORK

10. REFERENCES

[1] J. J. McAuley and J. Leskovec. From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews. In *World Wide Web*, 2013.

	# Examples	Variance	Linear Predictor	Collaborative Filtering	Latent Factor	Mahout ALS
Training	640135	0.049970	0.029748 **(0.404688)**	0.023681 **(0.526092)**	0.020354 **(0.592680)**	**(0.586866)**
Validation	160033	0.049826	0.033429 **(0.329085)**	0.033488 **(0.327886)**	0.030545 **(0.386954)**	**(0.392062)**
Test	200041	0.049818	0.033776 **(0.322010)**	0.033779 **(0.321948)**	0.030765 **(0.382451)**	**(0.388799)**

Table 1: MSE and R^2 obtained using the 3 predictors discussed in this work and Mahout's ALS recommender on the MovieLens dataset. Values in boldface/brackets are R^2 values.